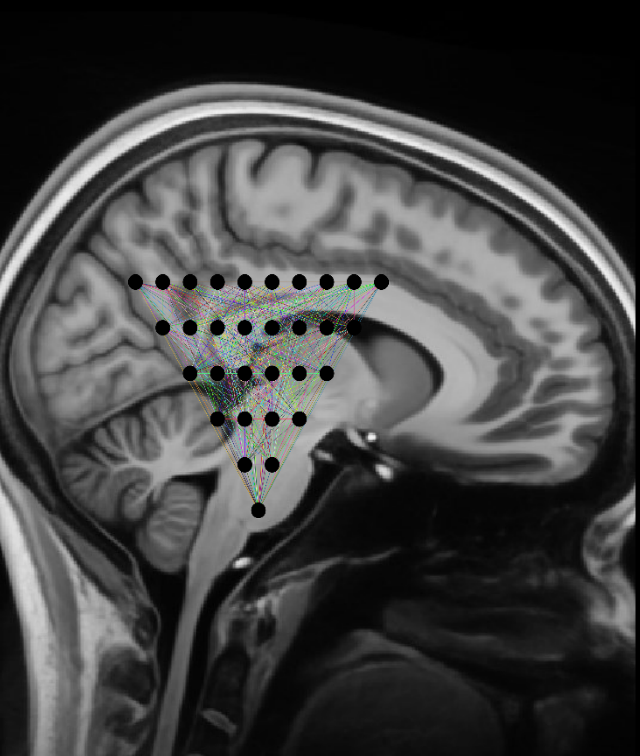
The physics of Magnetic Resonance Imaging and AI



Ludovic de Rochefort

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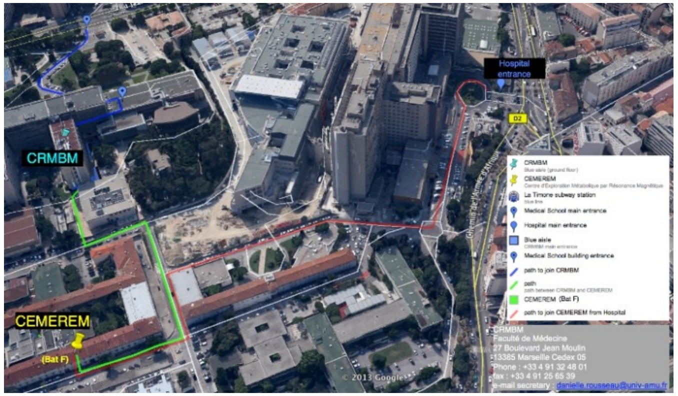
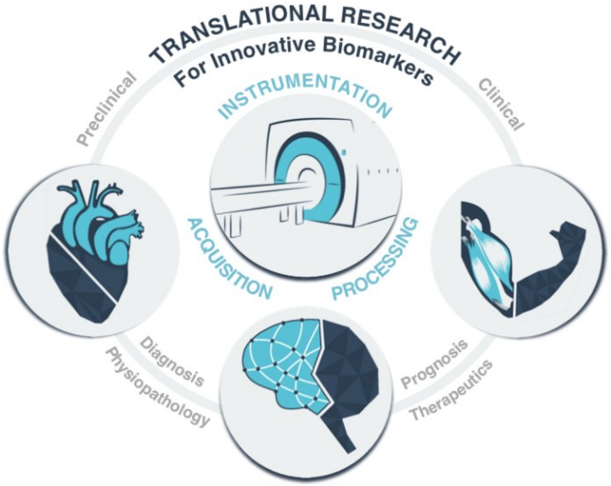
IA et Sciences physiques @ AMU – 22/11/2023

CRMBM- CEMEREM

- CNRS : INSIS, *INSB*, Section 28
- Aix-Marseille Université
- AP-HM





~70 people

Short Bio

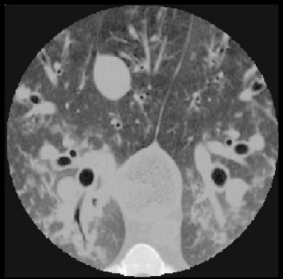
- PhD – Physics – Medical Imaging (2006)
- HDR – Physics – MR metrology (2014)
- CNRS researcher
- Research focusing on MRI physics and applications

Objectives

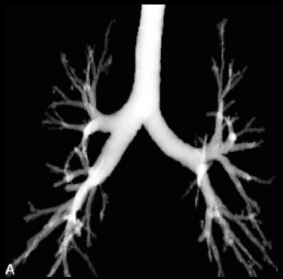
- Overview of (N)MRI multi-physics
- MR Images and AI
  - The depth of MRI contrasts
  - Traditional tasks that AI can solve
- MR raw signals and AI
  - The nature of MRI raw data
  - Overview of MRI acceleration strategies
  - Recent deep-learning reconstruction approach
  - Parallel imaging as a CNN super-resolution problem
  - Models to classify motion corrupted raw data

Morpho functional simulator of upper and central airways

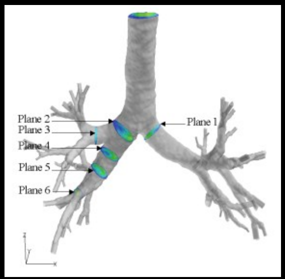
- R-Mod project (2001-2005), collaboration with Air Liquide



Lung CT



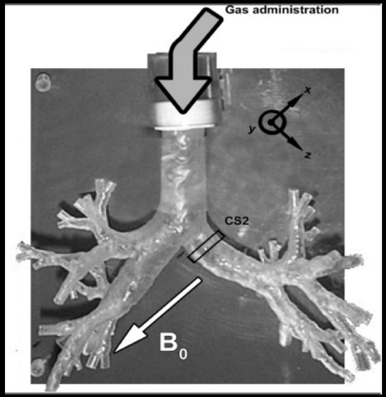
Segmentation



CFD
Patient-based model

Diagnostic tool
Particle deposition
Inhaled drugs

Hyperpolarized gas

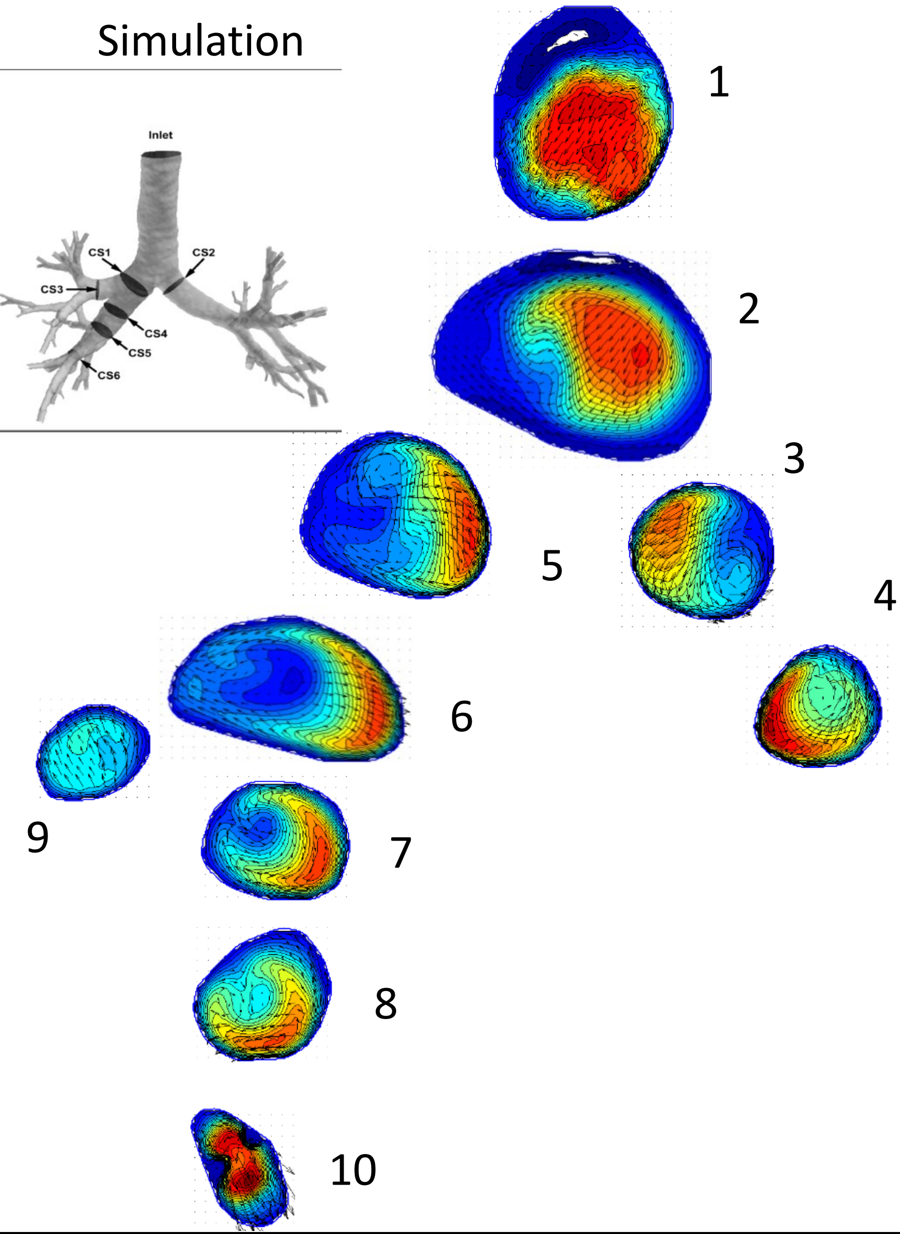


validation

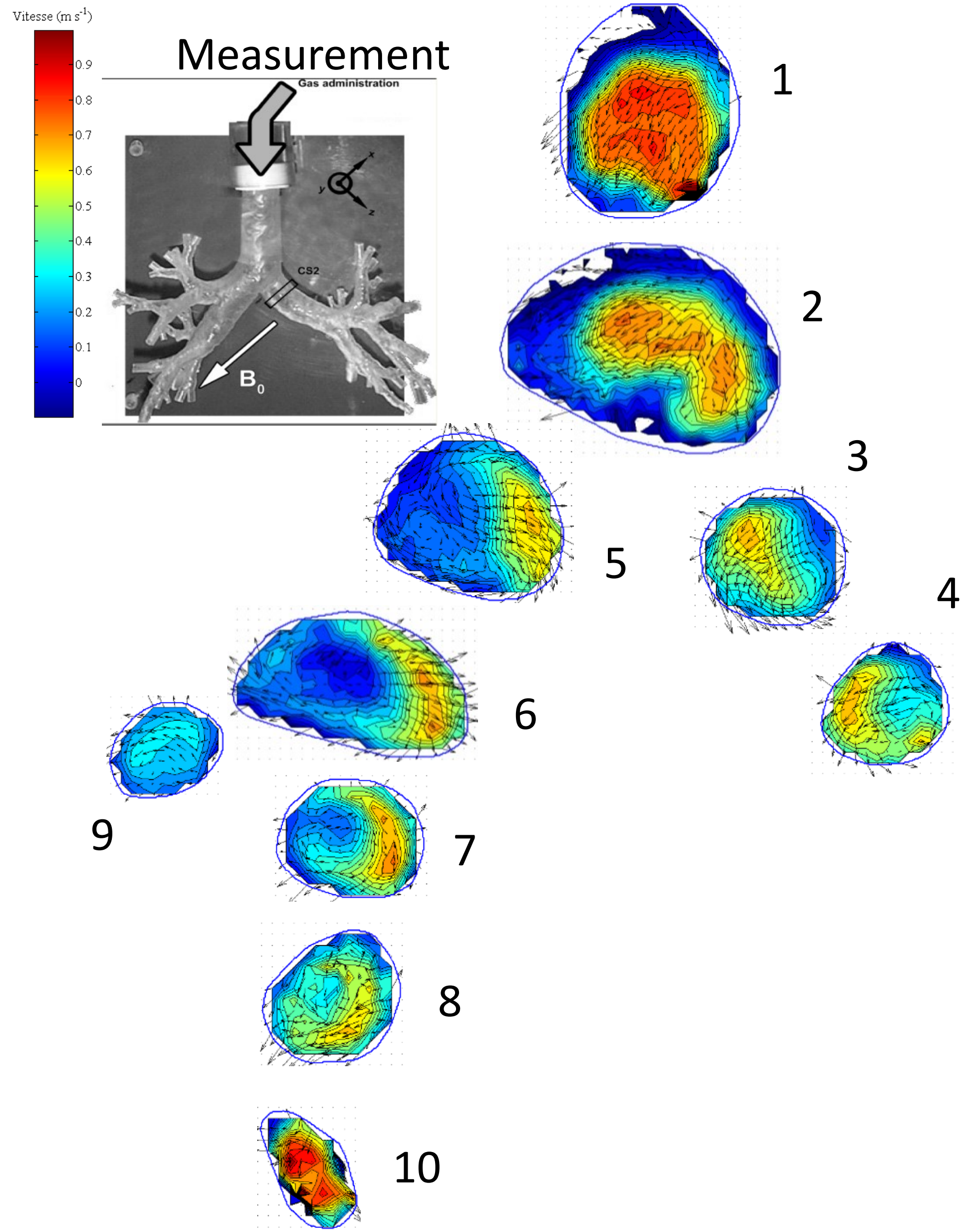
1. Fodil et al., *ITBM-RBM*, 26:72 2005.

de Rochefort et al., JAP 2007

Simulation



Measurement



Few physical aspects

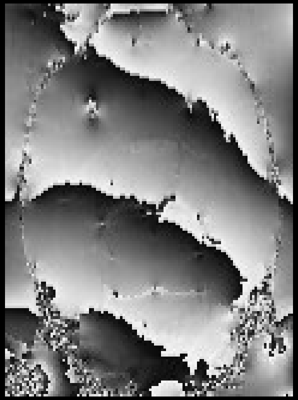
- Nucleus (^3He) – hyperpolarization
  - Quantum physics (spin, polarization)
  - NMR

- MRI velocity mapping
  - MRI pulse sequences

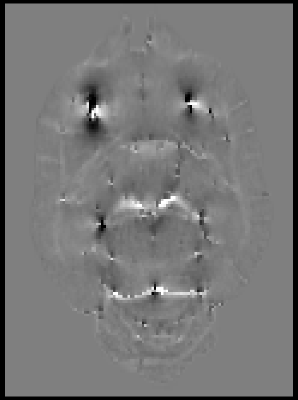
- Fluid mechanics
  - Navier Stokes equation

Quantifying magnetic susceptibility

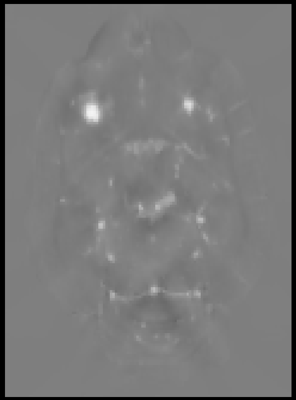
T2*W Amplitude



phase



Internal field



Magnetic source

The forward problem

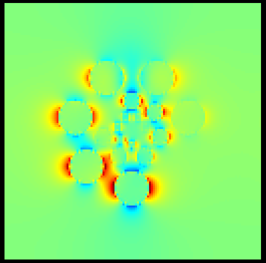
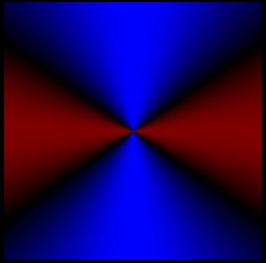
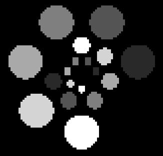
- Magnetostatic equation approximation, a partial derivative relationship

$$\frac{\Delta B_z}{B_0} = \frac{\Delta\chi}{3} - \frac{\partial^2\chi}{\partial z^2}$$

- Harmonic solutions

$$k^2 \times F\left(\frac{B_z}{B_0}\right) = \left(\frac{k^2}{3} - {k_z}^2\right) \times F(\chi)$$

- Fast field calculation

 $= F^{-1}\Big($  $\times\ F\Big($  $\Big)\Big)$

1. Haacke et al., 2005, MRI 23.
2. Salomir et al., 2003, CMRB, 19.
3. Marques et al., 2005, CMRB, 25.

The inverse problem

- Under-determined inverse problem,
  - Limited spatial and spectral information

- Various inversion approaches
  - inverse filter design[1]

$$X_r = \frac{\frac{1}{3} - \frac{{k_z}^2}{k^2}}{\left(\frac{1}{3} - \frac{{k_z}^2}{k^2}\right)^2 + \alpha^2} F\left(\frac{B_z}{B_0}\right)$$

  - minimization, prior knowledge[2,3]

$$\min_{\chi} \left\| W\left(D\chi - B_z/B_0\right) \right\|_2^2 + \alpha \left\| L\chi \right\|_p^p$$

1. Shmueli et al., MRM 2009
2. de Rochefort et al., MRM 2008
3. de Rochefort et al., MRM 2010

Few physical aspects

- Nucleus (^1H)
  - Quantum physics (spin, polarization)
- MRI physics
  - magnetic field mapping
- Magnetism
  - Magnetostatic
  - inverse problem
- Biophysics
  - Brain Iron

ABYSS

- Collaborative project (2011-2014) with Bertin technology, and Ecole vétérinaire de Maison-Alfort
- Ultra-fast induction of hypothermia in the context of rescucitated cardiac arrest, provides cardio- and neuro-protection[1]

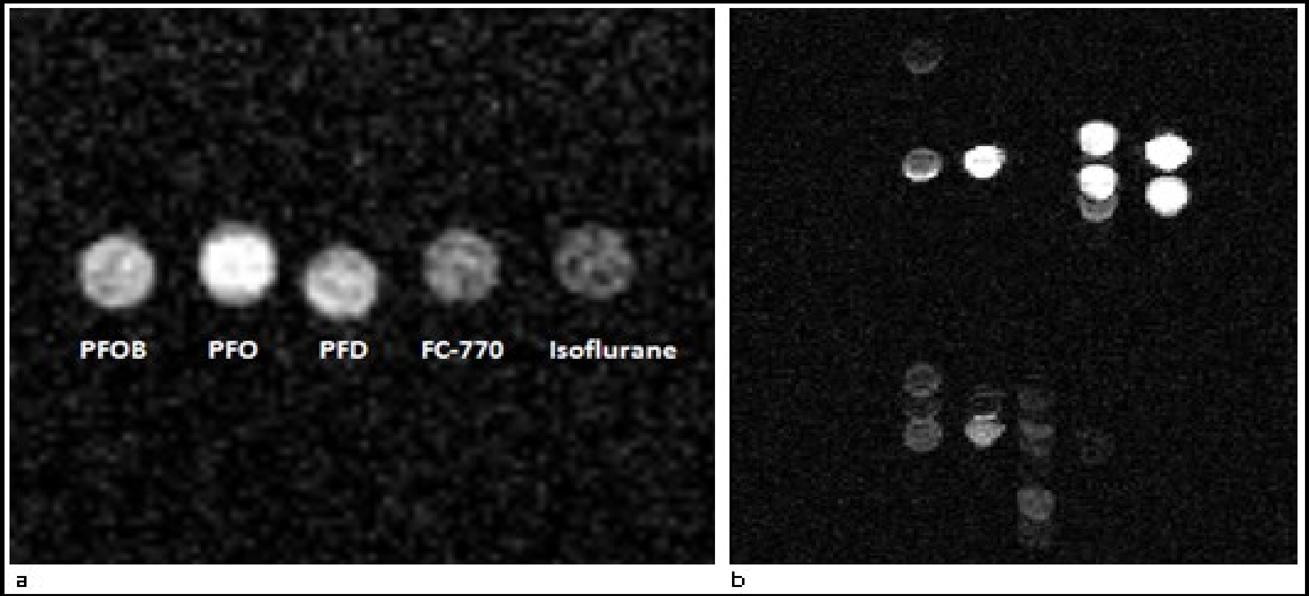
- Total Liquid Ventilation (TLV)
- using inert perfluorocarbons (PFC)
- maintain gas exchanges
- enable ultra-fast hypothermia

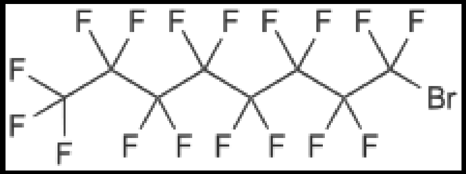
From ABYSS (1989), James Cameron

1. Tissier R, et al., J Am Coll Cardiol. 2007; 49:601

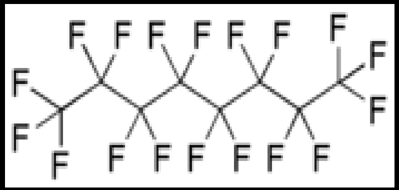
Perfluorocarbon imaging

- T_1~1s / T_2~50 ms-1s / J-coupling
- Complex spectrum for imaging

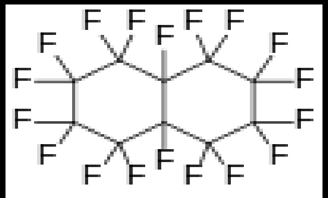




perfluorooctylbromide (PFOB)



Perfluorooctane (PFO)



Perfluorodecalin (PFD)

Few physical aspects

- Nucleus (^{19}F)
  - Quantum physics (spin, polarization)
  - Homonuclear NMR – J-coupling
- NMR relaxation
  - pulse sequences
  - Relaxation time (coherence time)
- Fluid mechanics
  - Incompressible, fluid structure coupling
  - System engineering
- Biophysics
  - Ventilation
  - Heat transfer

NMR for quantum computing

- Liquid NMR has been used for quantum computing
- Large Fluorine molecules with J-coupling can be used as n-qubit systems (up to ~10)
- Can be used as testbed for quantum algorithms (ex. Grover)

➢ Rising research topic : quantum ML for MRI?

1. Nielsen and Chuang, Quantum Computation and Quantum Information, 2010 Ch.7.7

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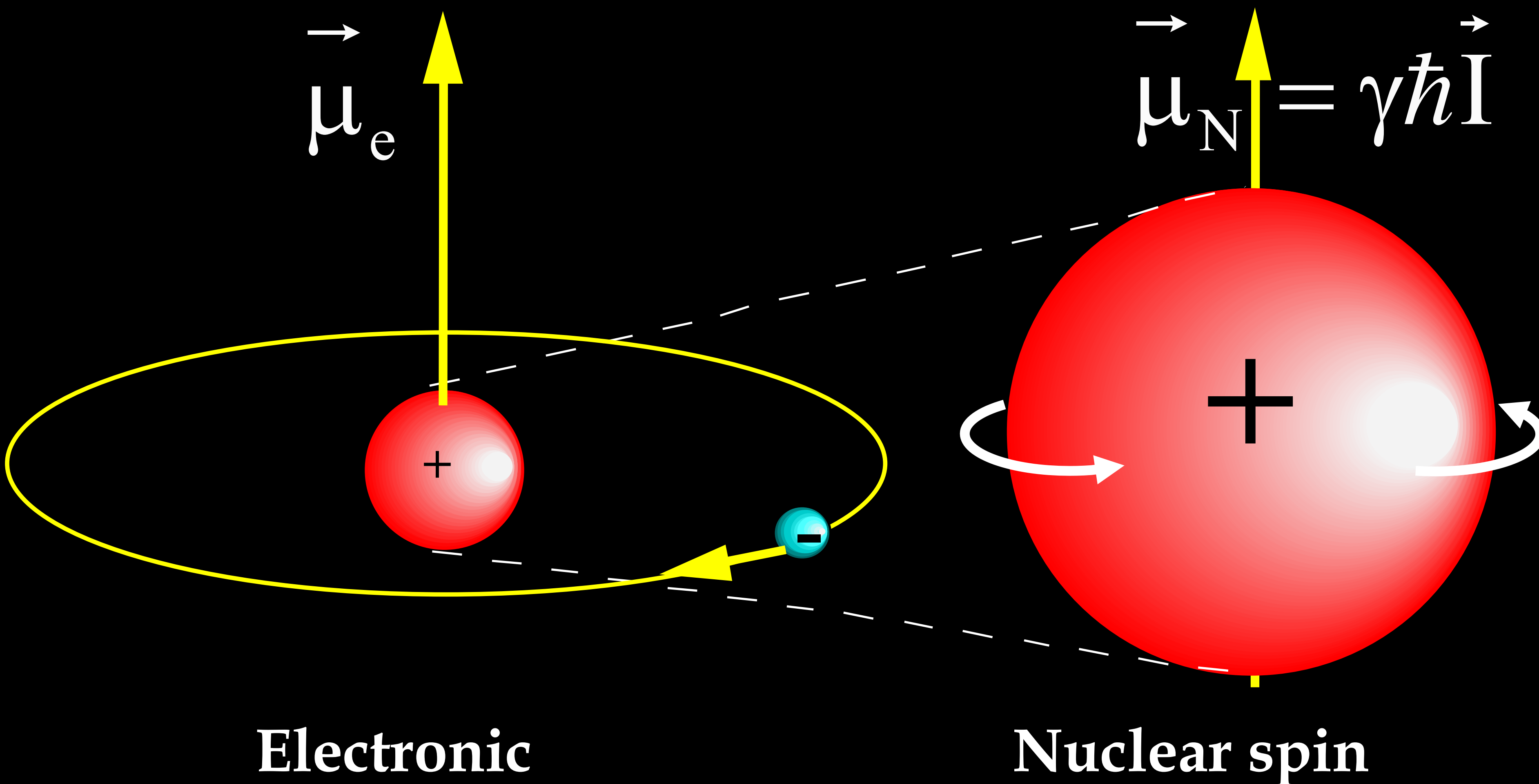
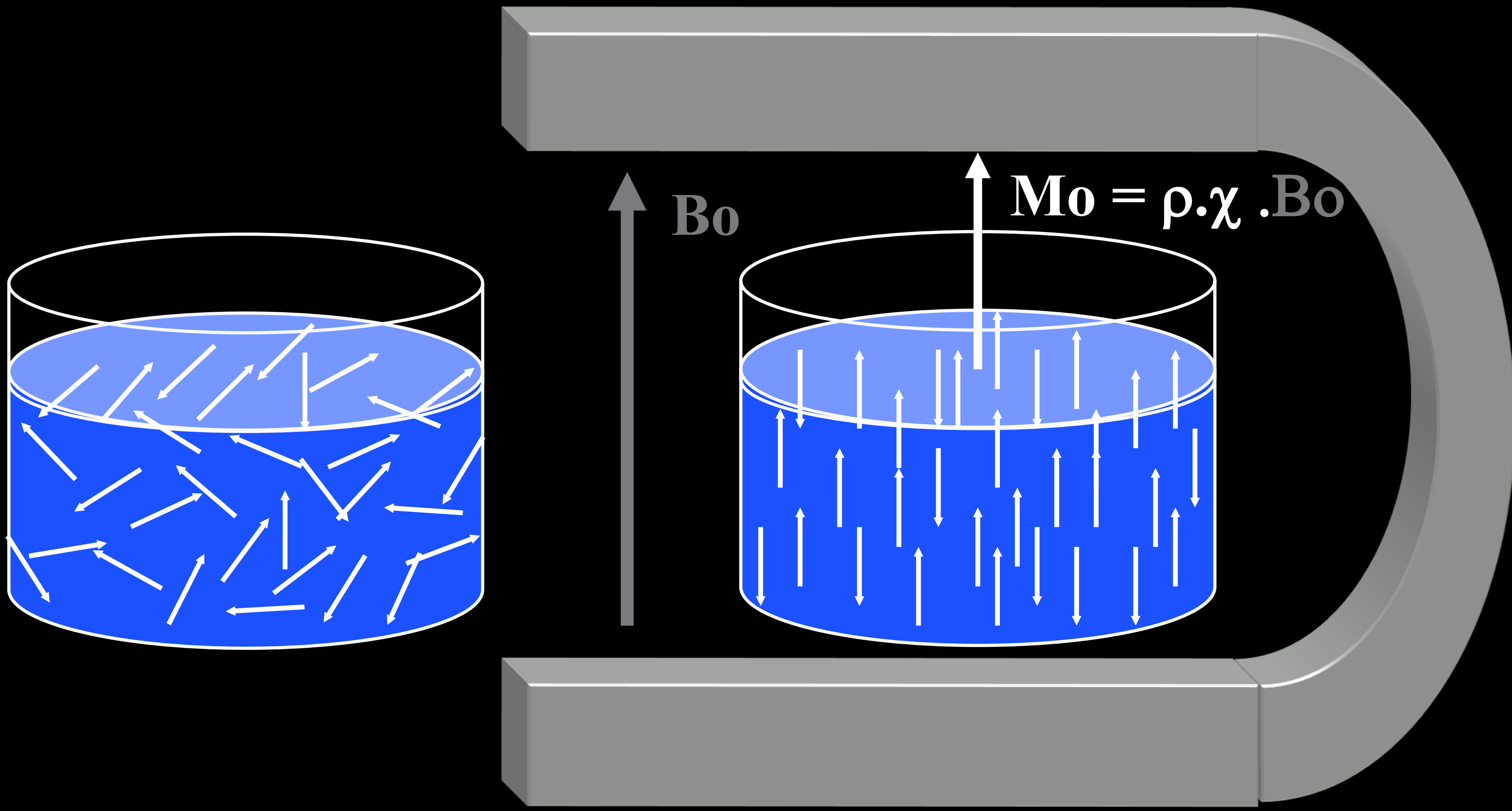
Nuclear origin



Magnetization

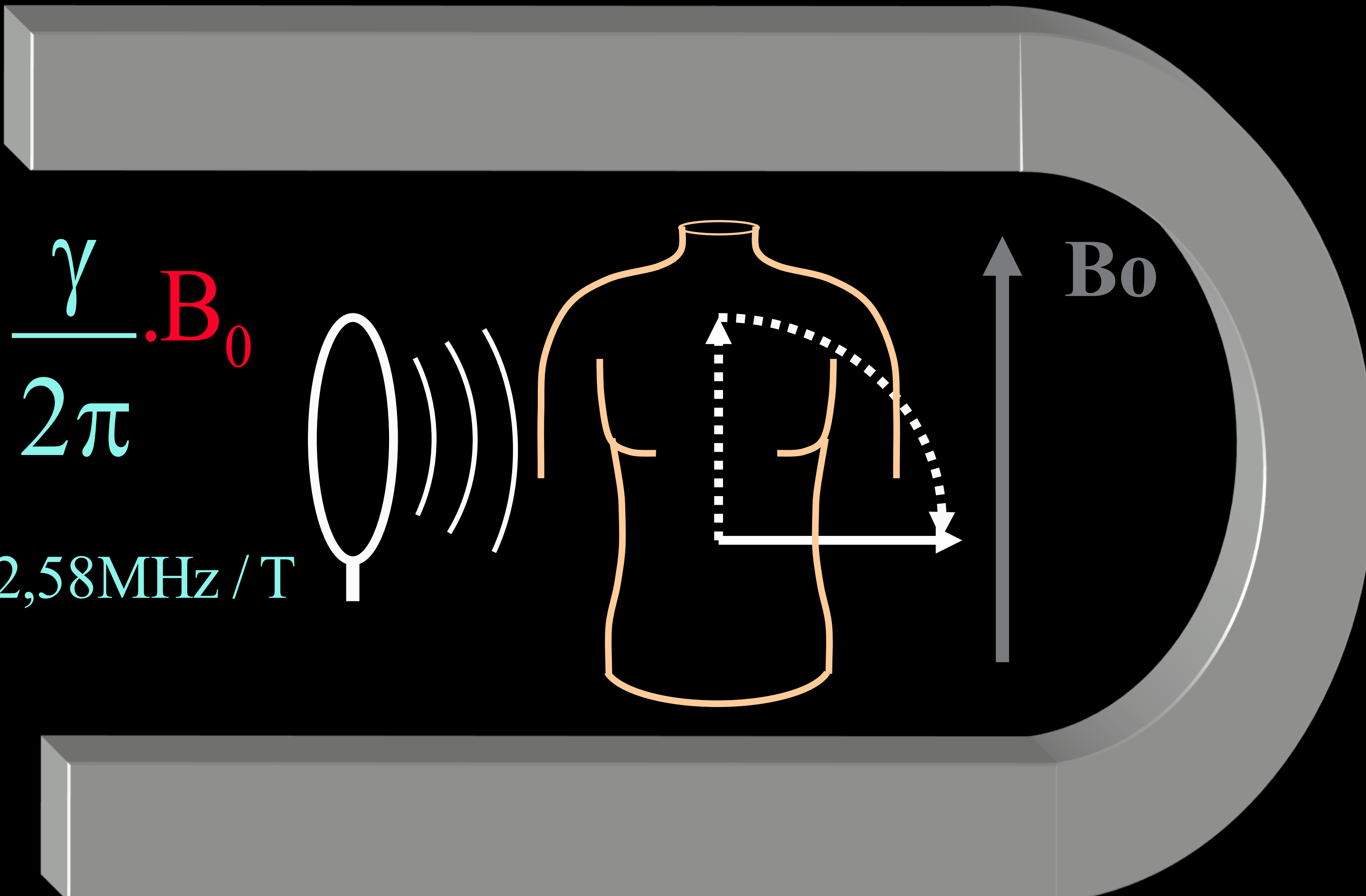


Magnetization (Boltzmann equilibrium)
Proportional to the magnetic field B_0 (at thermal equilibrium)

Larmor frequency - excitation

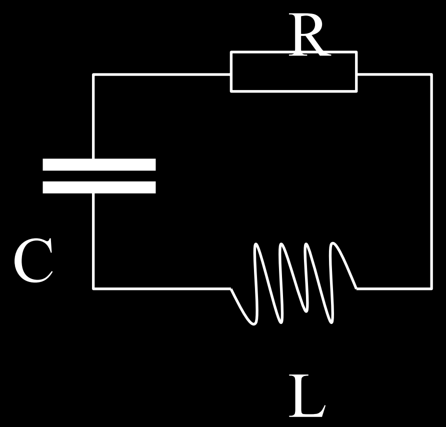
$$f_0 = \frac{\gamma}{2\pi} . B_0$$

$$\frac{\gamma_H}{2\pi} \approx 42{,}58 MHz / T$$



Resonance – difference between energy levels

Radiofrequency coil



Low frequency
Quasi-static approximation
(Biot and Savart law)

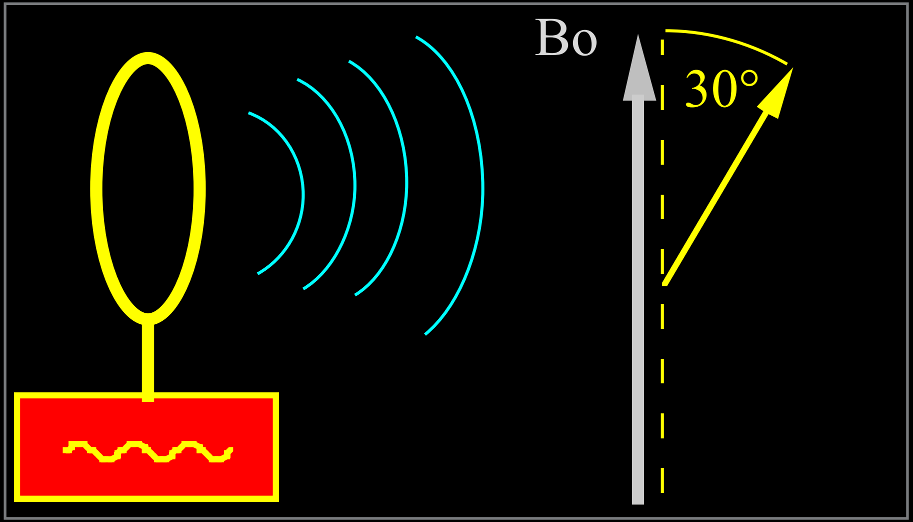
Tuned for a given nucleus

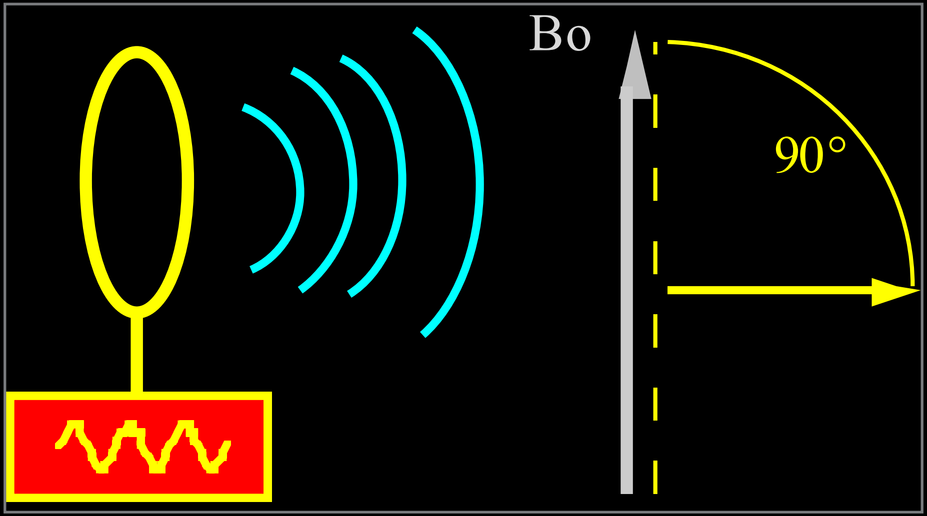
Nucleus	$\gamma/2\pi$ (MHz/T)	Natural abondance(%)	Relative sensitivity
^{1}H	42,58	99,98	100
^{19}F	40,03	100	83
^{3}He	32,43		
^{31}P	17,23	100	6,6
^{23}Na	11,26	100	9,3
^{13}C	10,70	1,1	$1,6.\ 10^{-2}$

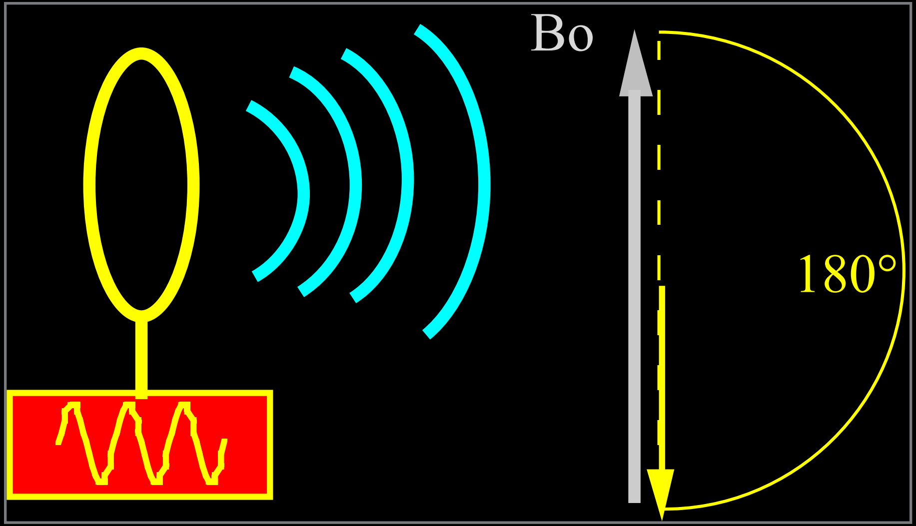
Flipping the magnetization

$$f_0 = \frac{\gamma}{2\pi} \cdot B_0$$

$$\frac{\gamma_H}{2\pi} = 42{,}58\, MHz / T$$



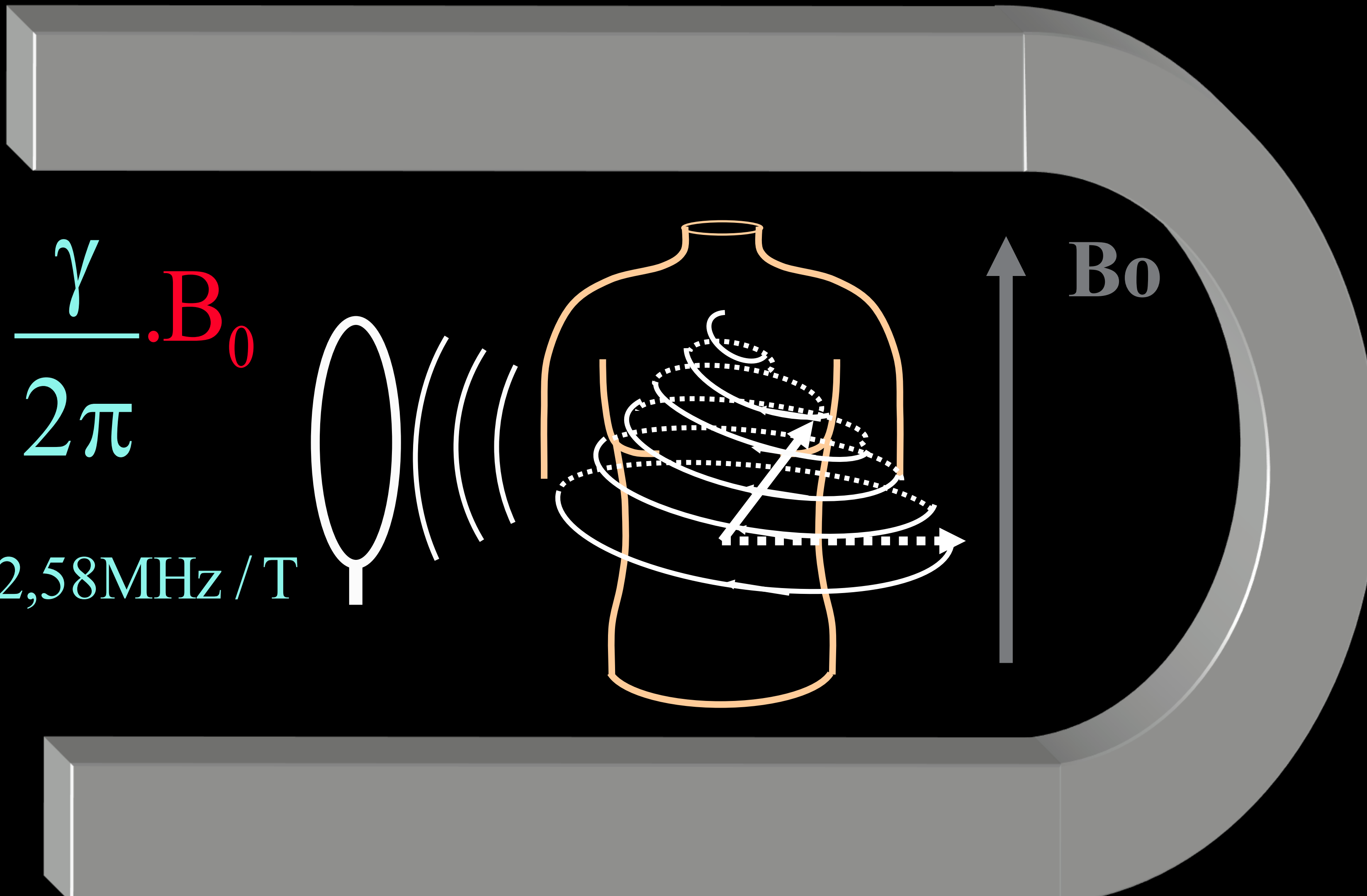




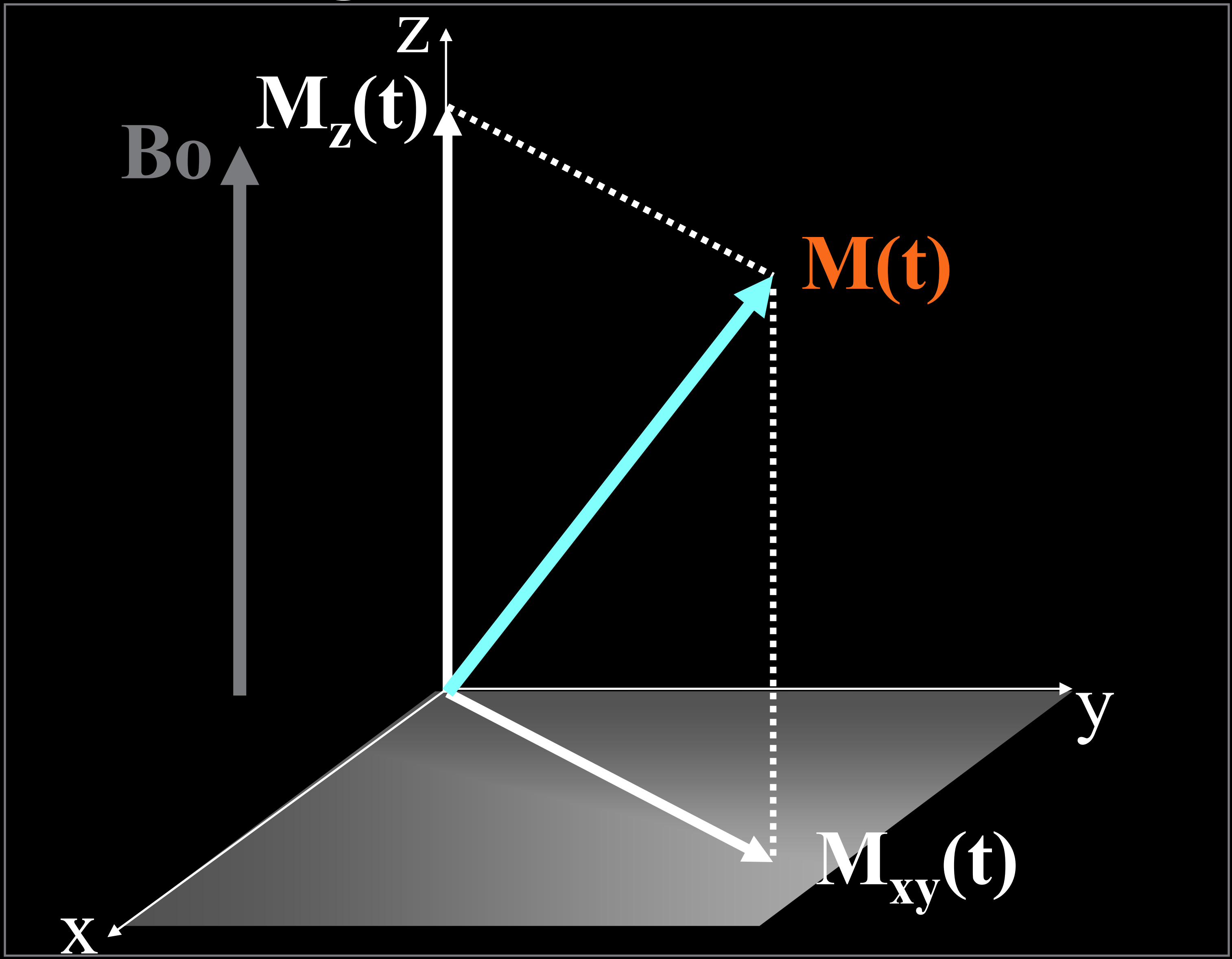
Back to thermal equilibrium

$$f_0 = \frac{\gamma}{2\pi}.B_0$$

$$\frac{\gamma_H}{2\pi} \approx 42{,}58\,\mathrm{MHz} / \mathrm{T}$$



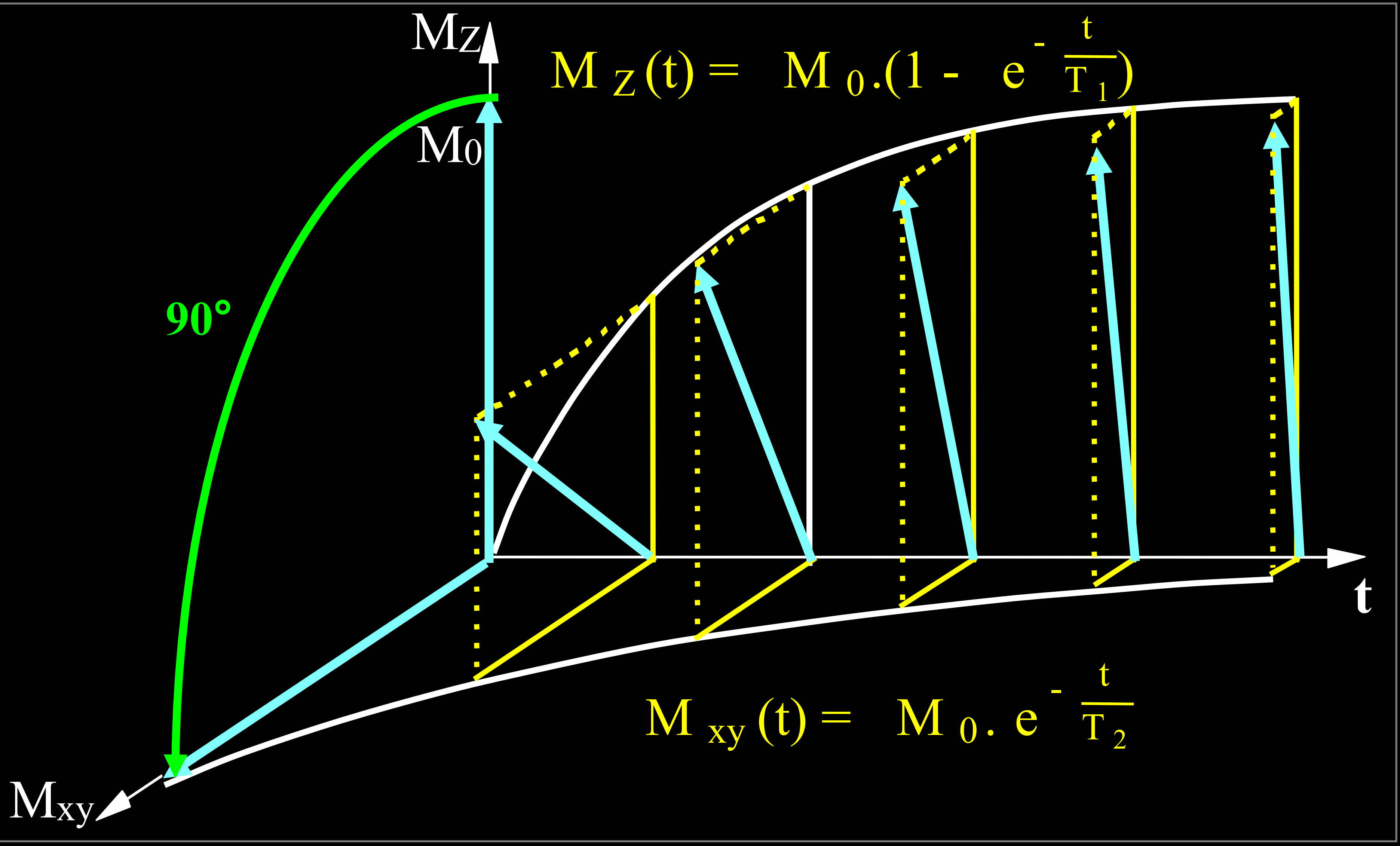
Magnetization vector



Bloch equations

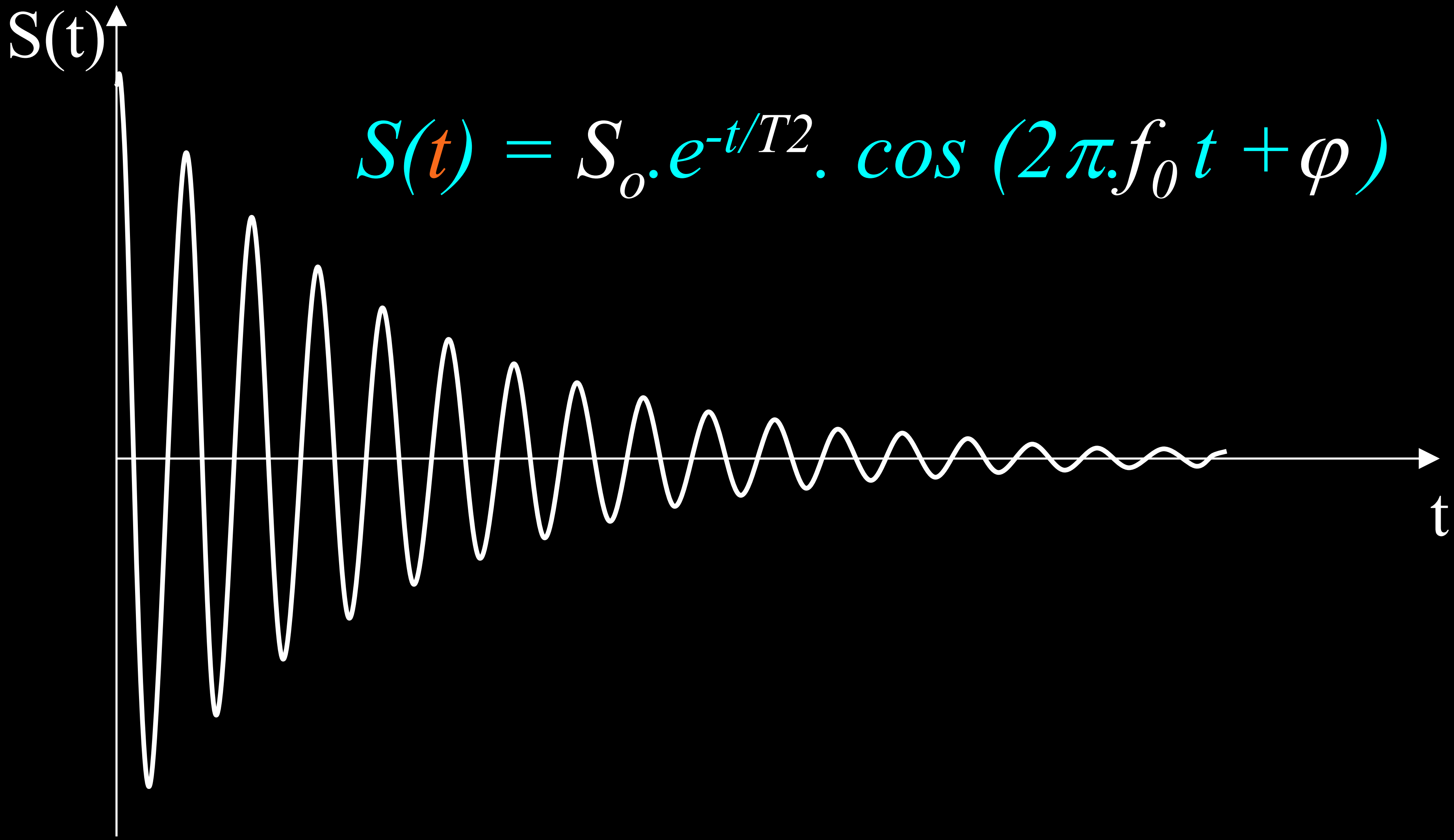
$$\frac{d\overrightarrow{M(t)}}{dt} = \gamma \overrightarrow{M(t)} \times \overrightarrow{B(t)} - \begin{pmatrix} M_x(t) / T_2 \\ M_y(t) / T_2 \\ (M_z(t) - M_0) / T_2 \end{pmatrix}$$

- Several tools can be used to handle ‘rotations’
  - 3D/4D Matrix description
  - Spinors, quaternions, ‘configuration states’, …



M_Z
$M_Z(t) = M_0.(1 - e^{-\frac{t}{T_1}})$
M_0
90°
t
$M_{xy}(t) = M_0 . e^{-\frac{t}{T_2}}$
M_{xy}

Free induction decay



$$S(t) = S_o . e^{-t/T2} . \cos(2\pi . f_0 t + \varphi)$$

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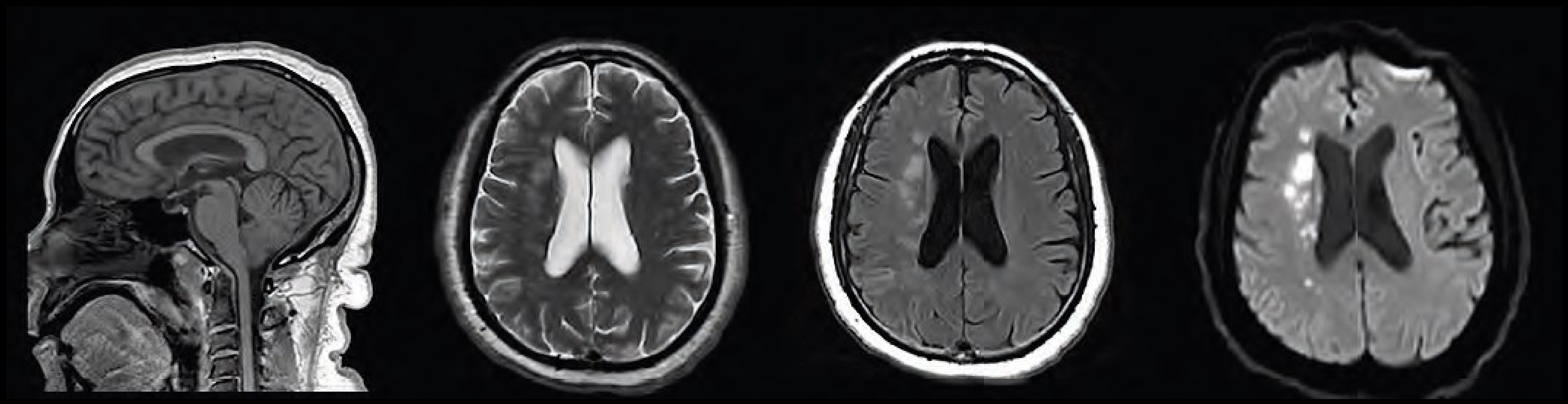
The depth of MRI contrats



T1W	T2W	FLAIR	DWI
anatomy	mobile water	Removing CSF	Restricted diffusion

- MRI uses water molecules as a sensors
- It provides a variety of contrasts
- It is sensitive to tissue structure and content

➢ Can be used as inputs to various data models for image-related tasks

Traditional tasks in Image domain

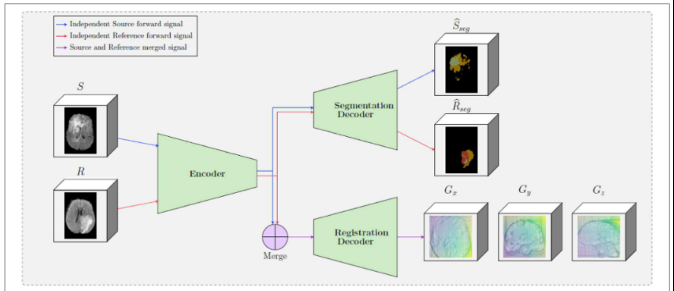


FIGURE 1 | A schematic representation of the proposed framework. The framework is composed by two decoders, one which provides tumor segmentation masks for both *S* and *R* images, and one the provides the optimal displacement grid *G* that will accurately map the *S* to the *R* image. The merge bloc will combine the forward signal of the source input and the reference input (which are forwarded independently in the encoder).

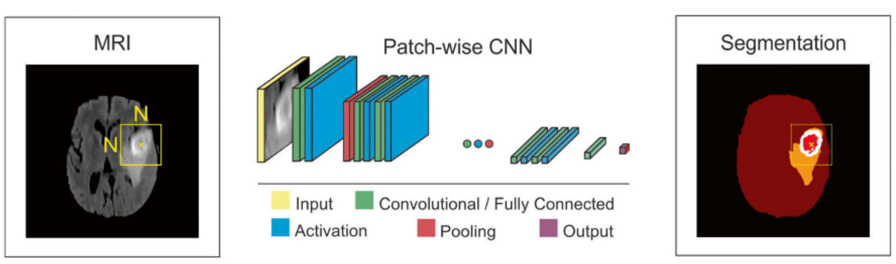
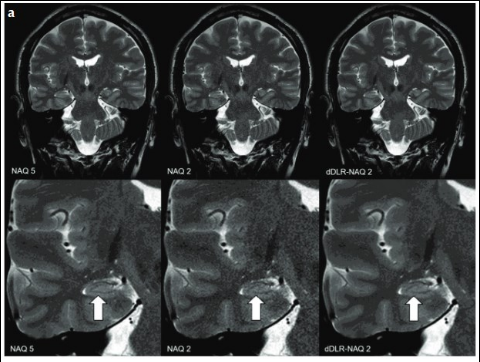


Image registration / segmentation / classification[1,2,3]



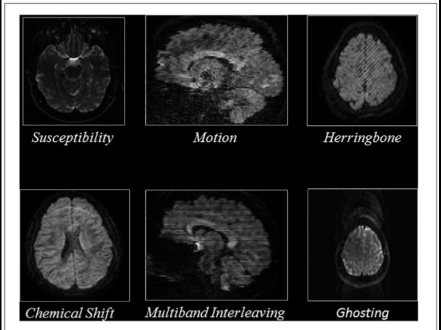


FIGURE 1 | Representative slices of the different artifacts that the QC-Automator was trained to detect.

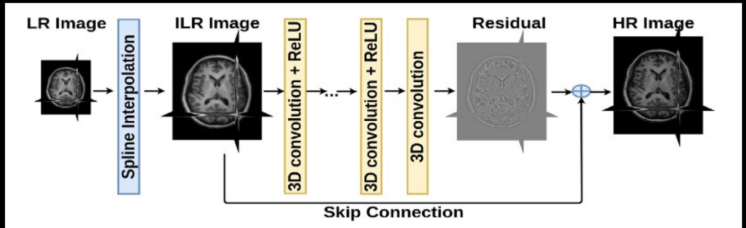


Fig. 1. 3D deep neural network for single brain MRI super-resolution.

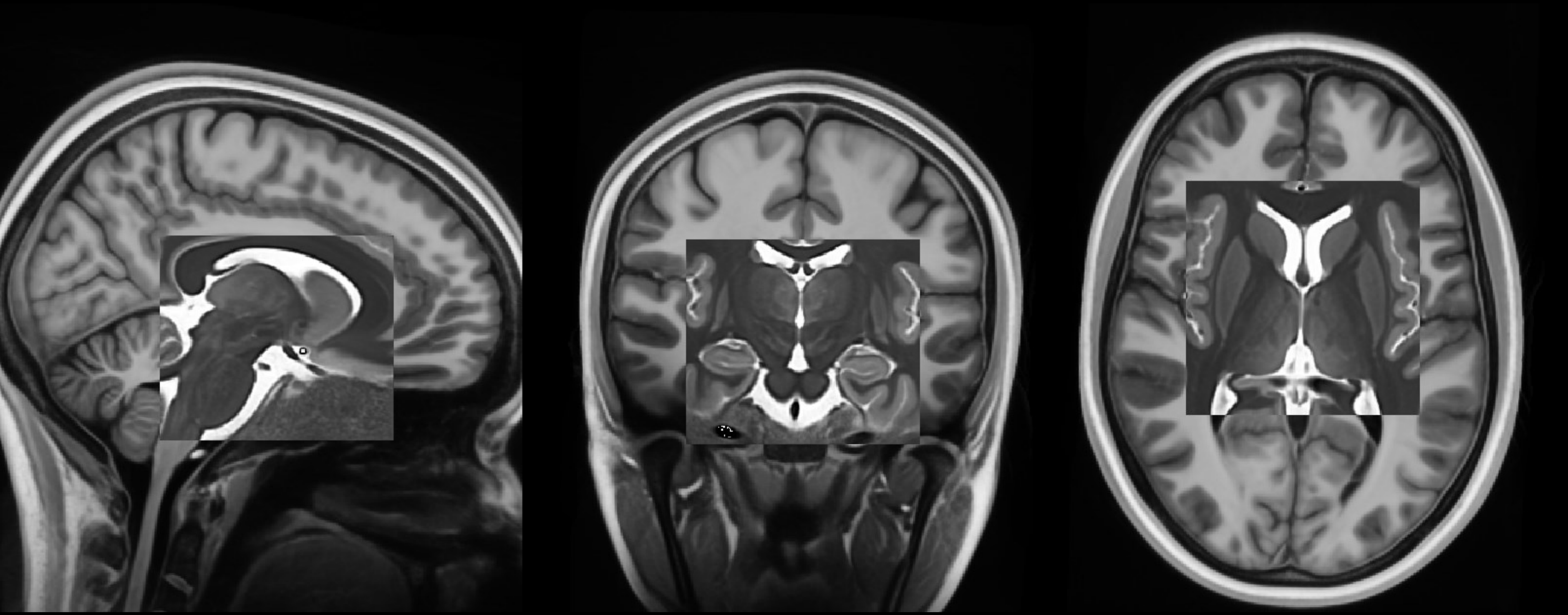
Image denoising[4]

quality control[5]

super-resolution[6]

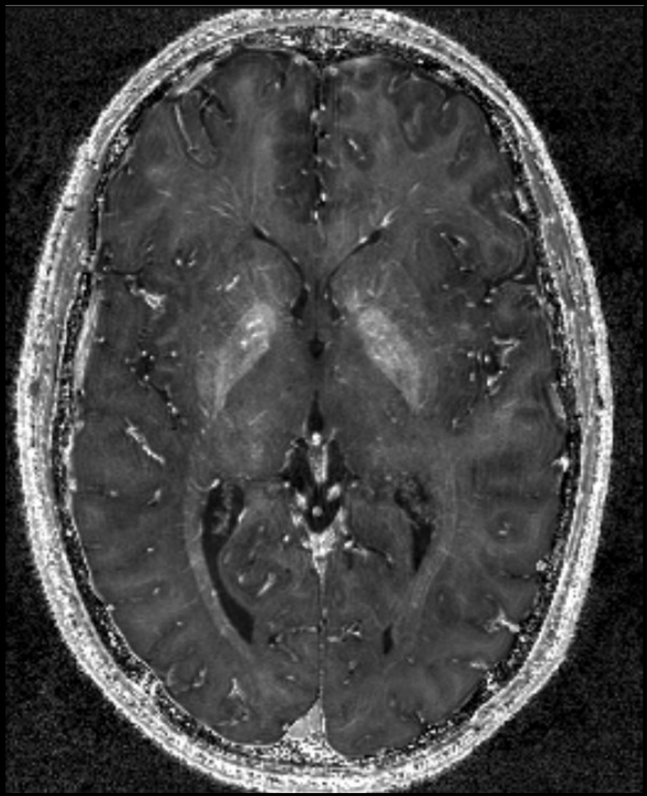
[1]Estienne et al., Front Comput Neurosci 2020,
[2]Akkus et al., J. Digit Imaging, 2017, doi: 10.1007/s10278-017-9983-4
[3]Nagaraj et al., Sensors, 2020, doi: 10.3390/s20113243
[4]Kidoh et al., MRMSci 2020, doi:10.2463/mrms.mp.2019-0018
[5]Samani et al 2020 Front Neurosci, doi: 10.3389/fnins.2019.01456
[6]Pham et al, Comp Med Im Graph, 2019, doi:10.1016/j.compmedimag.2019

Spatial resolution vs acquisition times

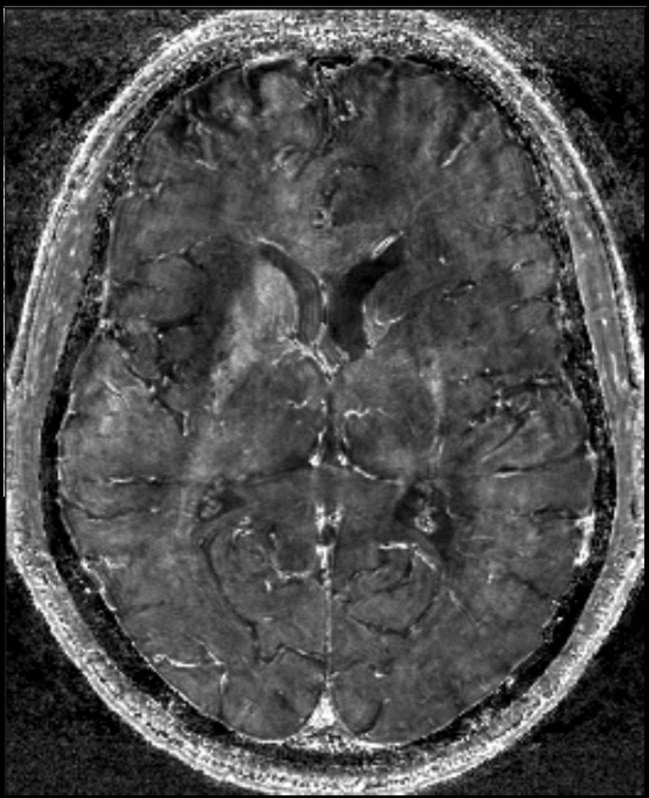


- MRI generates highly resolved 3D data (at UHF) providing exquisite details of brain structure and function
- However, the acquisition process takes time
- ➢ Not feasible for all desired contrasts, and sensitive to motion

Spatial resolution vs acquisition times



Limited motion artifacts



Large motion artifacts

- Motion reduced image quality and resolution
- Problematic in many clinical applications
- Reducing acquisition time is a major issue

Spatial resolution vs acquisition times

- Need for methods in order to:
  - ➢ Shorten scan time without sacrificing resolution
  - ➢ Correct for motion for long scans

➢ Can AI models do it?

➢ How to adapt AI models to the nature of MRI data?

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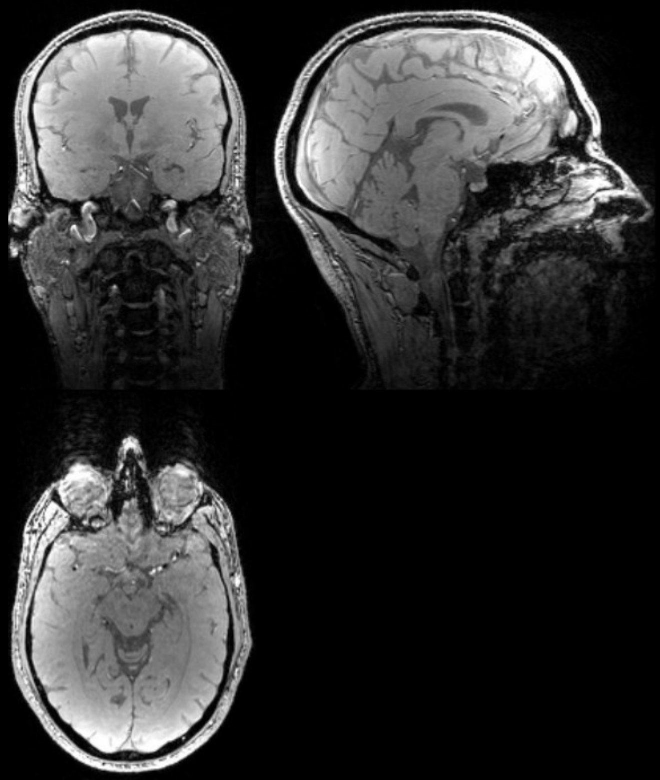
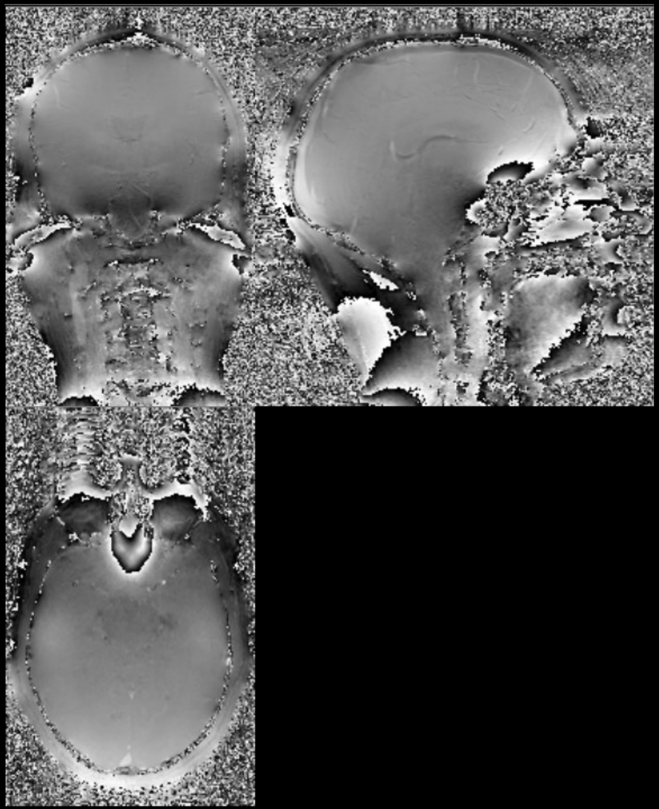
MRI data is complex



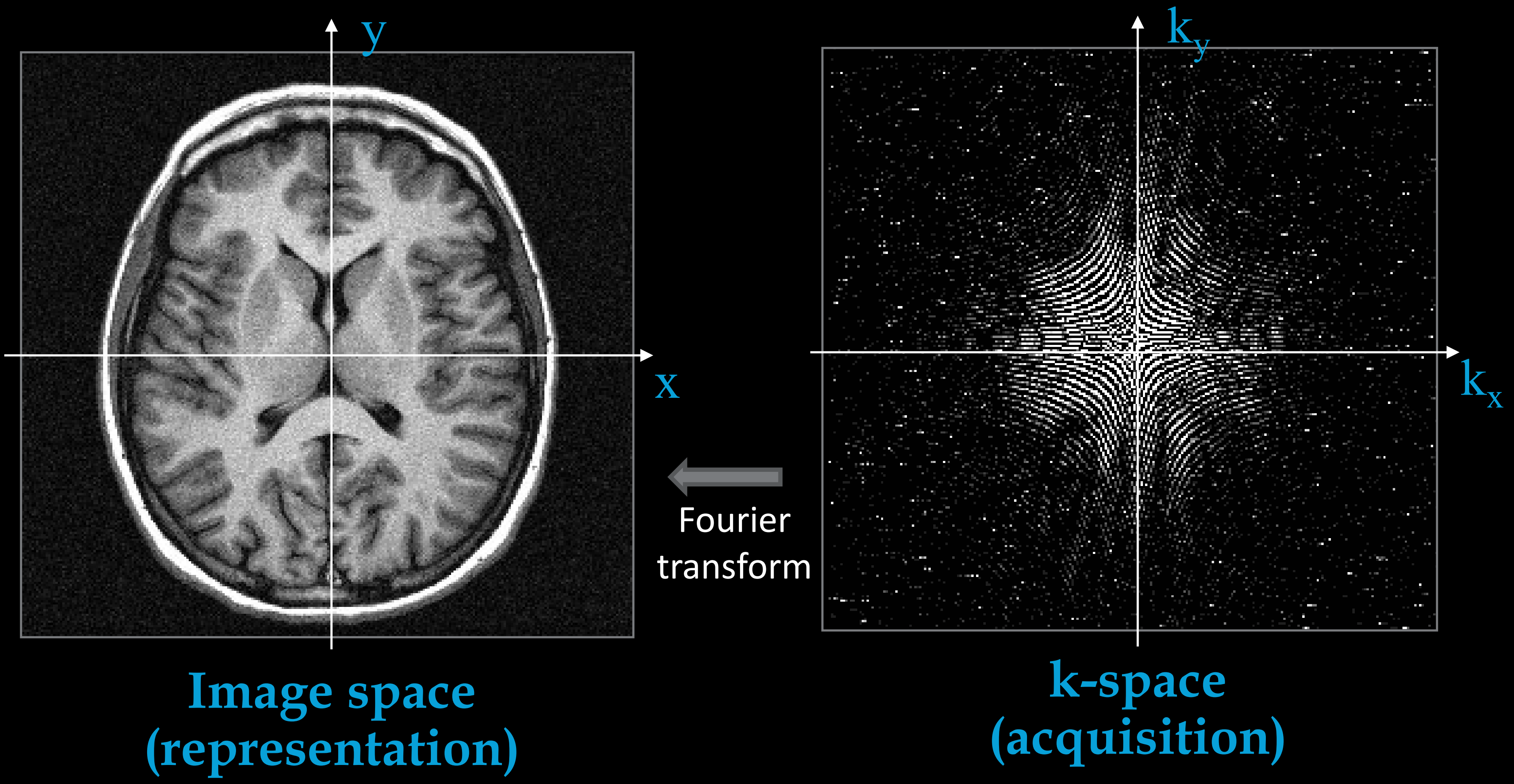


Magnitude

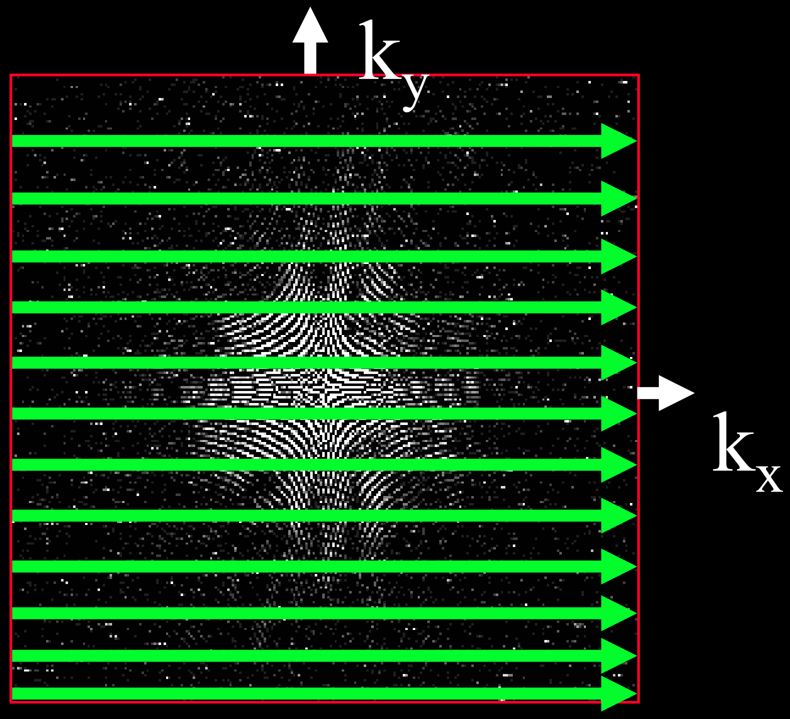
Phase

$$M\left(x,y,z\right)=\left|M\left(x,y,z\right)\right|\exp\left(i\varphi\left(x,y,z\right)\right)$$

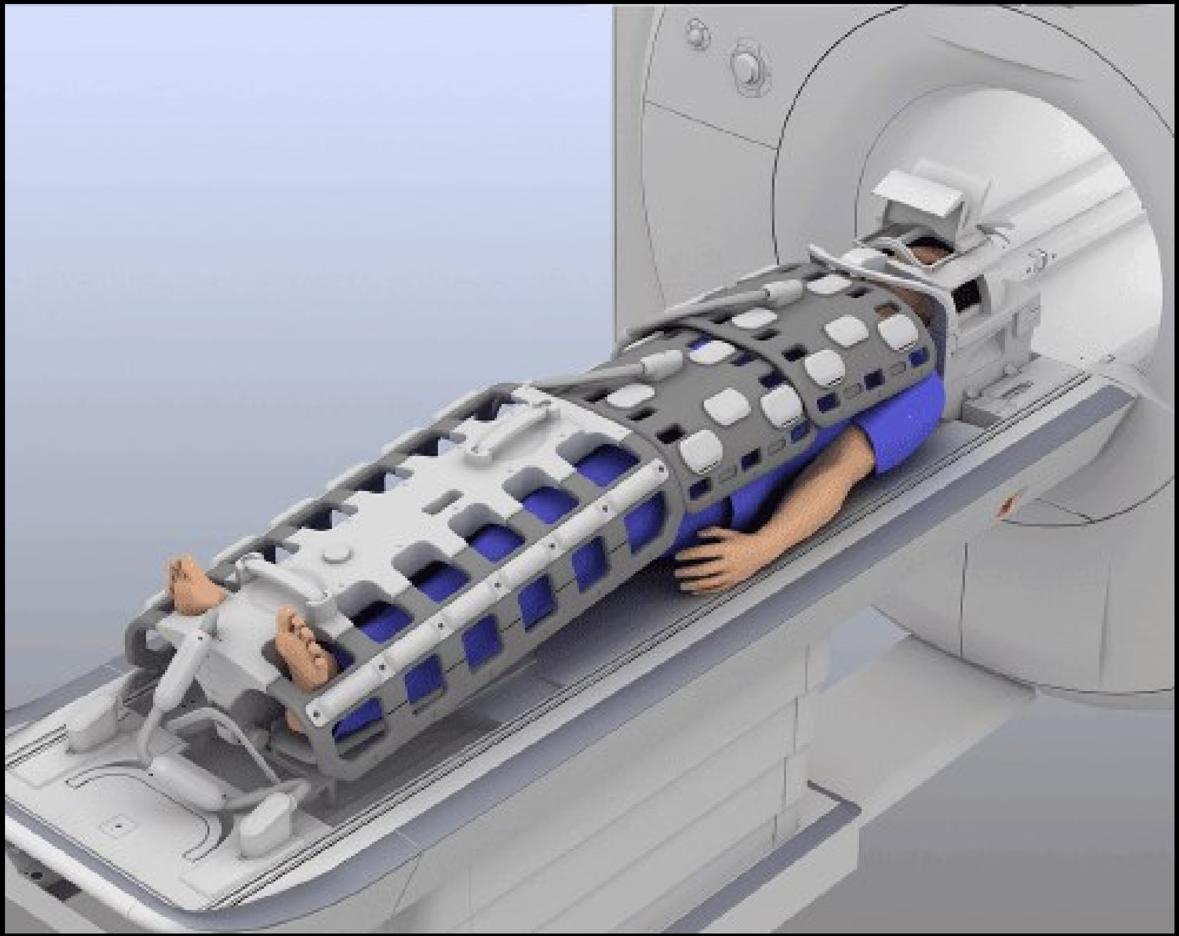
MRI raw data is acquired in k-space



k-space is sampled sequentially



MRI raw data is using several sensors



MRI data is intrinsically Big

- 3D k-space typically 256^3
- Complex data – (float 32 bits)
- Coils (sensors) typically 20-64
- Contrasts – typically 4-8
- Time – 20-32

➢ Between ~100 Gb to ~2 Tb if sampled exhaustively !

➢ With a high degree of redundancy

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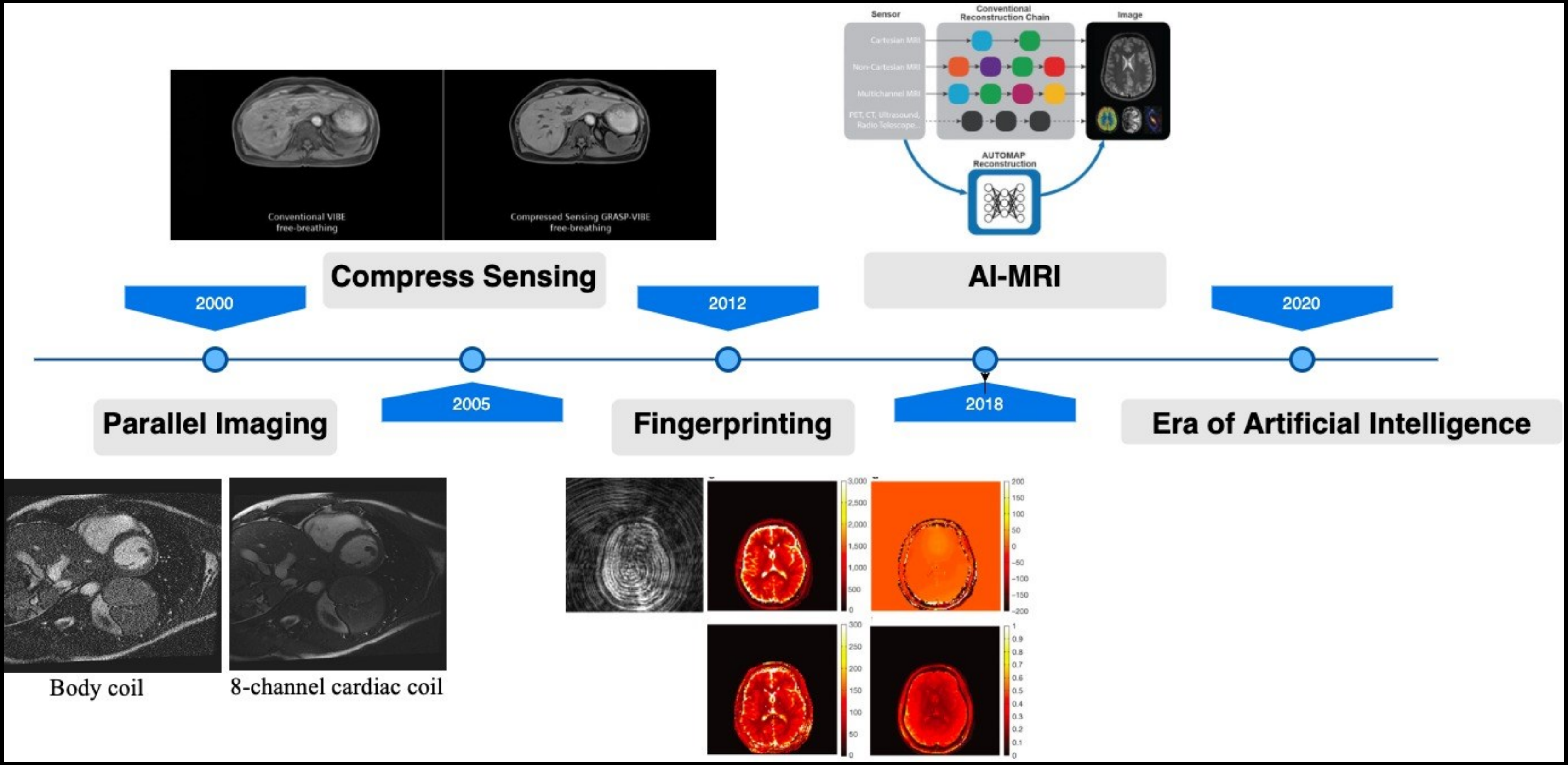
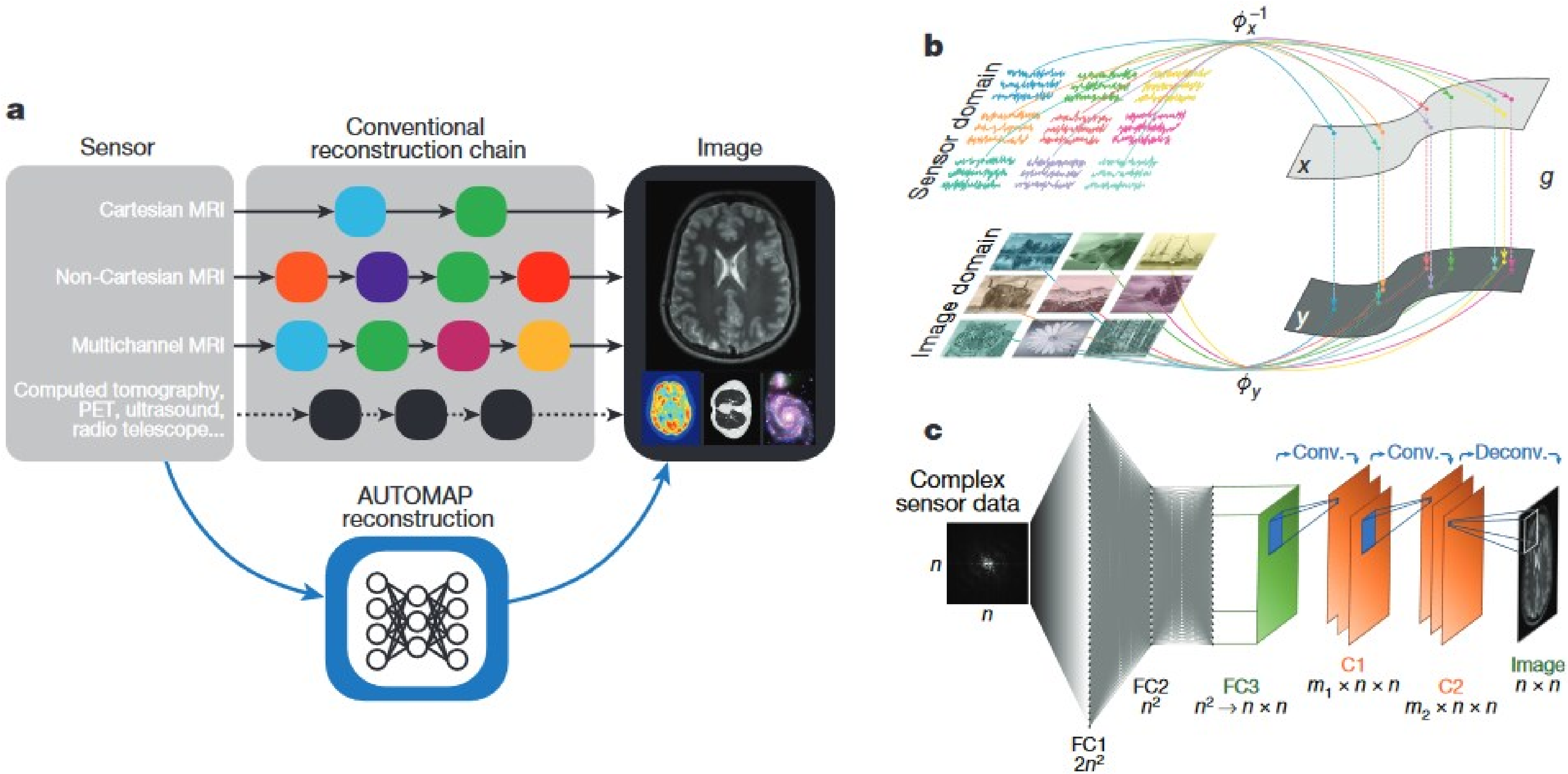
Overview - MRI acceleration strategies



Shared general principles:

1 – undersampled k-space = reduce acquisition time
2 – add knowledge and make use of redundant information

Image reconstruction with AI



Automap, model based on a full knowledge of the acquisition process / imaging setup

Zhu, Nature 2018, doi: 10.1038/nature25988.

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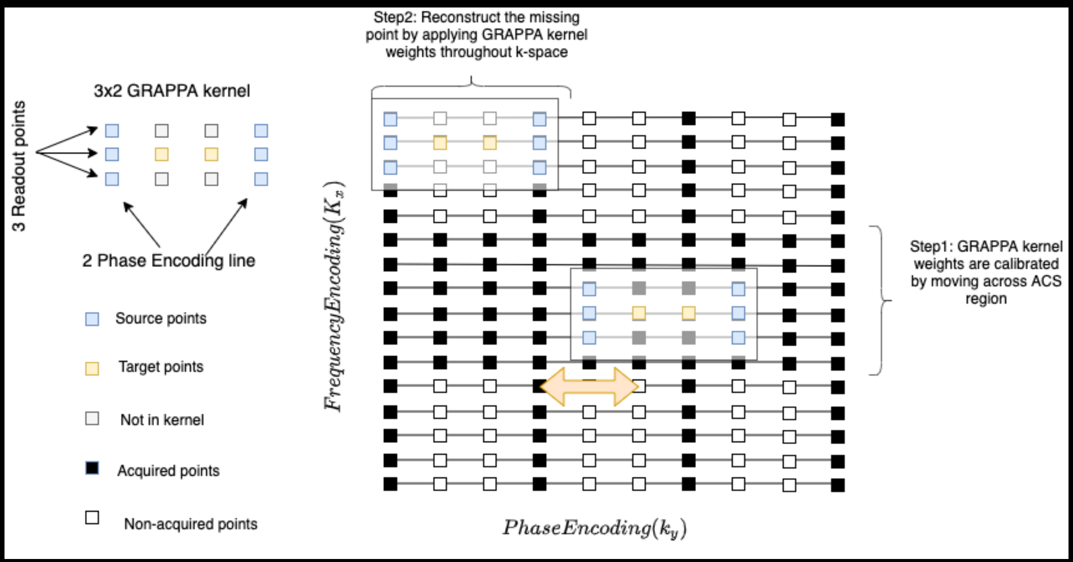
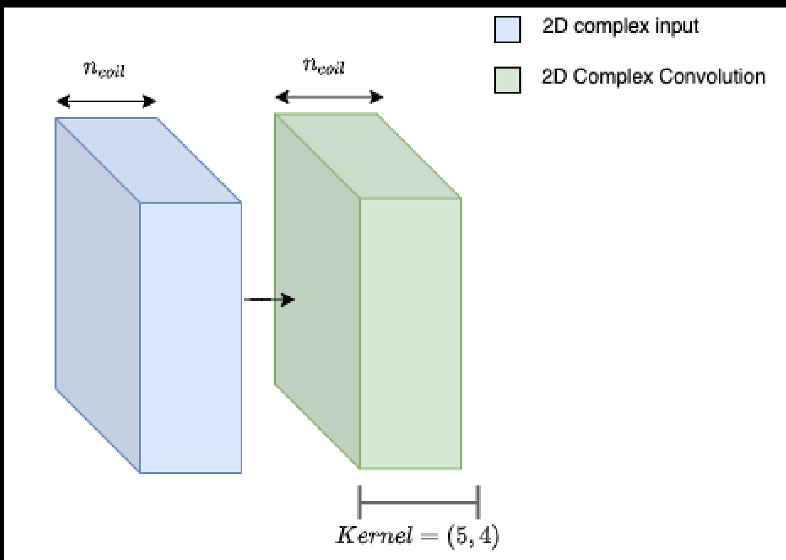
Machine learning to accelerate acquisition and reconstruction of multiparametric brain Magnetic Resonance Imaging"

Swetali NIMJE, PhD thesis

Supervision:
T. Artières (QARMA, LIS)
L. de Rochefort (CRMBM)

Parallel imaging



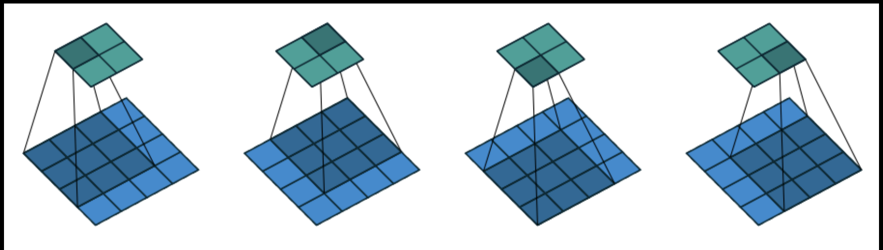


Parallel imaging is equivalent to a training a CNN data model based on examples to solve a super-resolution task in k-space

Griswold MA et al. Magn Reson Med. 2002 Jun;47(6);1202-10.

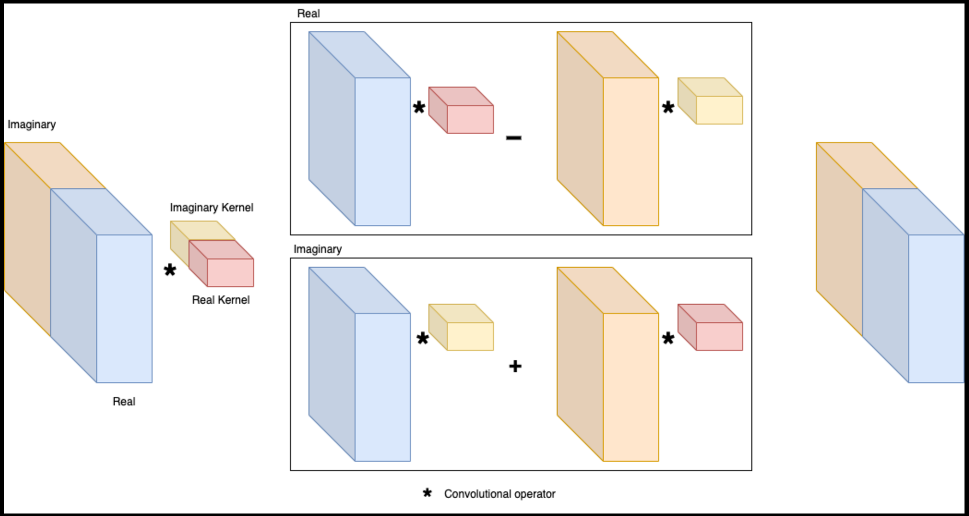
Complex convolution layers

Real Convolution

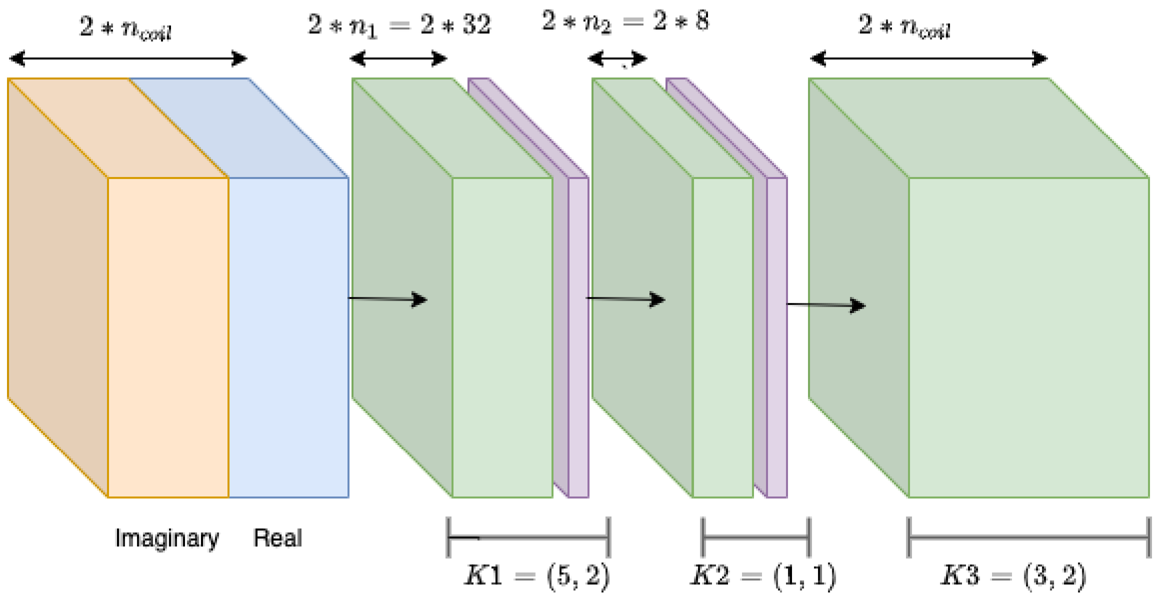


*Convolving a 3 × 3 real kernel over a 4 × 4 real input using unit strides

Complex Convolution



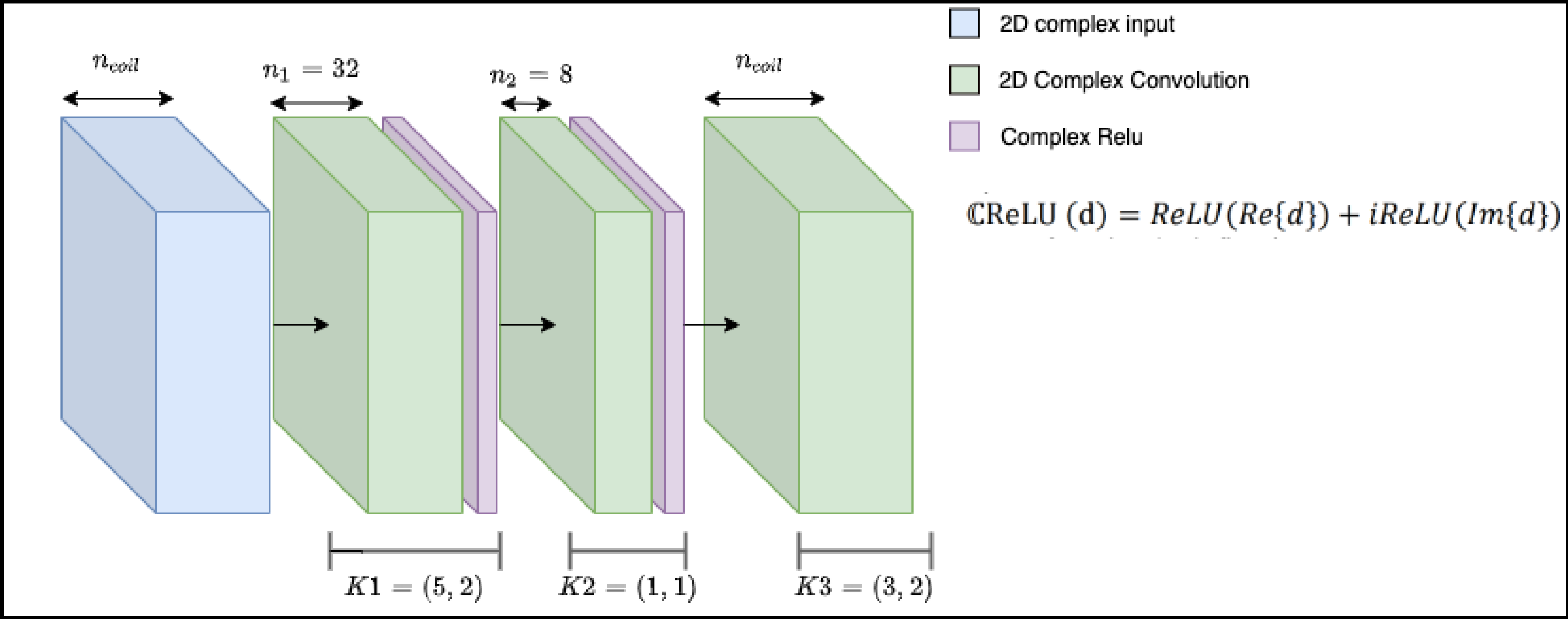
Scan-specific data models



$$ReLU(d) = \begin{cases} d, & if\ d \geq 0 \\ 0, & otherwise \end{cases}$$

Akçakaya , Magn. Reson. Med 2019, 10.1002/mrm.27420

Scan-specific data models

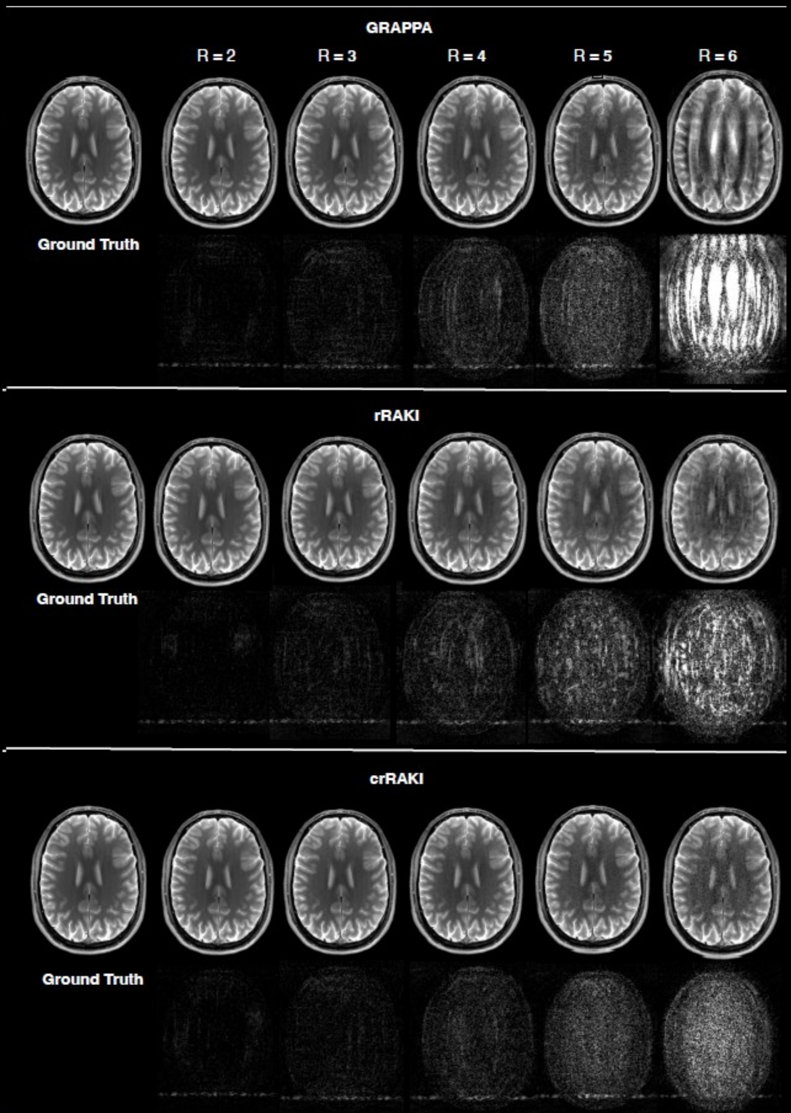


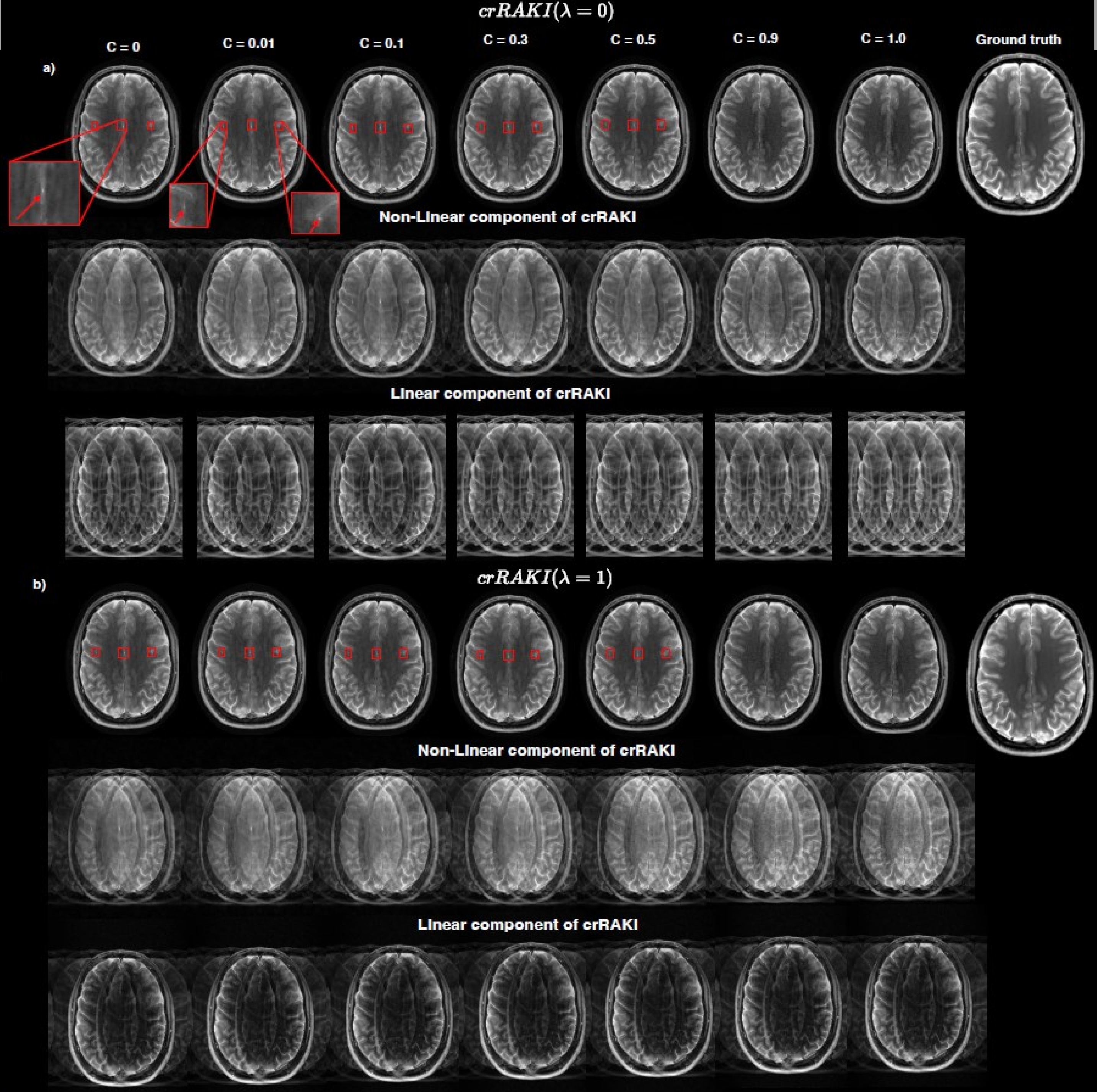
Complex formulation

Scan-specific data models

T2W 2D FSE on a volunteer

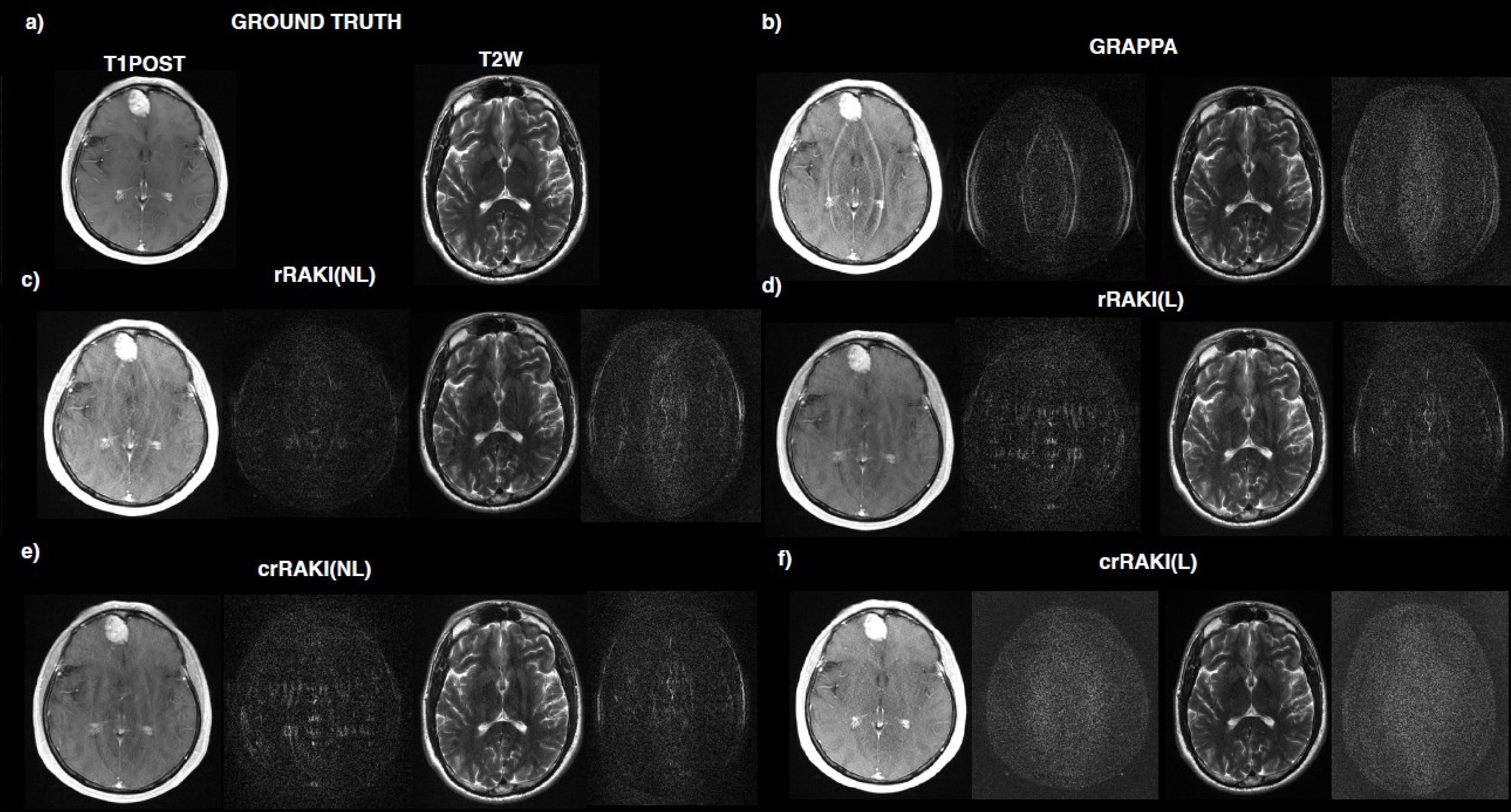
Typical acceleration in practice
R = 2, 3





$crRAKI(\lambda = 0)$
C = 0
C = 0.01
C = 0.1
C = 0.3
C = 0.5
C = 0.9
C = 1.0
Ground truth
a)
Non-Linear component of crRAKI
Linear component of crRAKI
b)
$crRAKI(\lambda = 1)$
Non-Linear component of crRAKI
Linear component of crRAKI

Scan-specific data models



Scan-specific data models - conclusions

- Scan-specific complex-CNN models can be trained
- Considering one acquisition embedding the training data
- Exploiting intrinsic redundancy
- Adapting model architectures and training strategies to this specific problem
- Results indicate the possibility to reduce scan time as compared to traditional approaches

Objectives

- MR Images and AI
  - The depth of MRI contrasts
  - Traditional tasks that AI can solve
- MR raw signals and AI
  - The nature of MRI raw data
  - Overview of MRI acceleration strategies
  - Recent deep-learning reconstruction approach
  - Parallel imaging as a CNN super-resolution problem
  - Models to classify motion corrupted raw data

Correction of motion using deep-learning

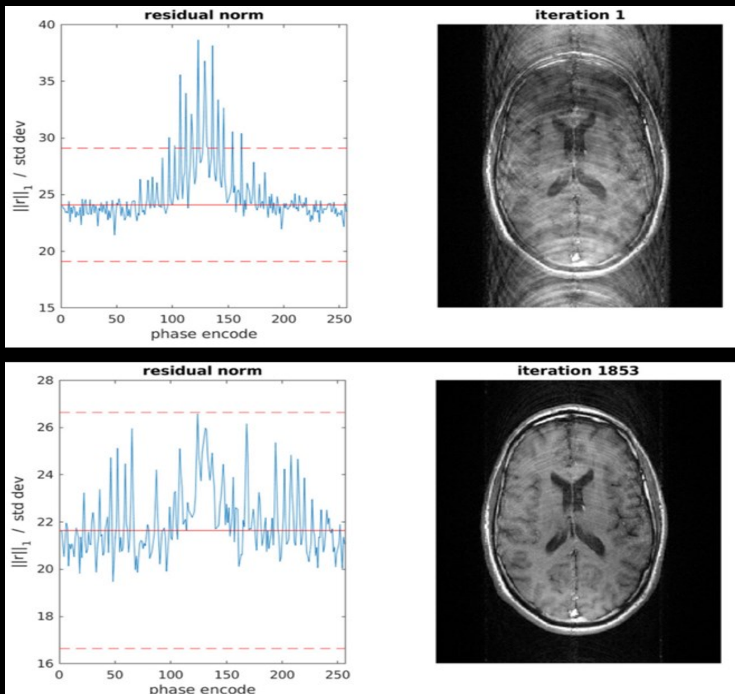
CRMBM-CEMEREM UMR 7339

SIEMENS Healthineers

Jérémy Beaumont, post-doctoral researcher

Supervision:
T. Troalen (Siemens Healthineers)
L. de Rochefort (CRMBM)

Motion correction using TAKE



TAKE is a technique that uses:

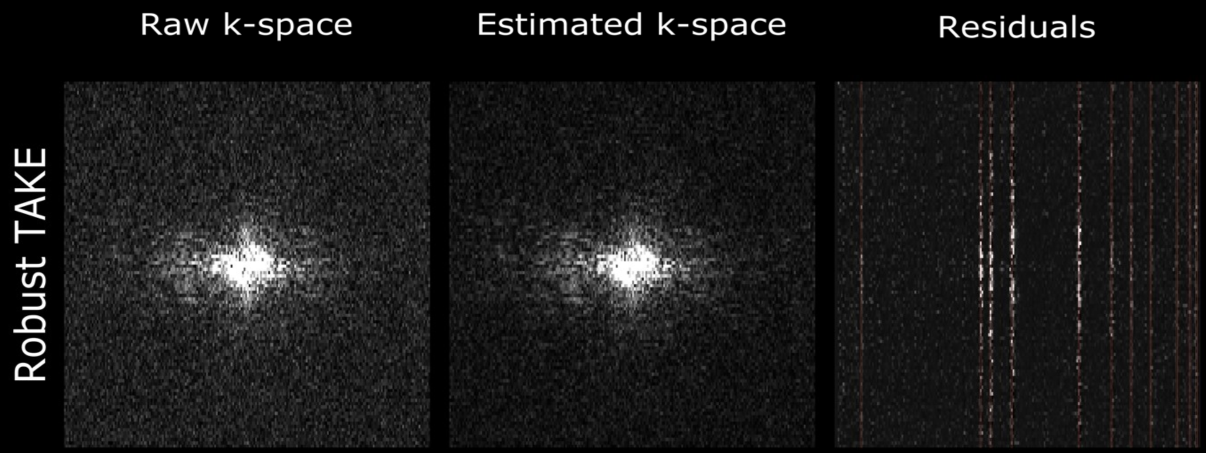
- data consistency between neighbors
- expressed as local convolution filter
- an Hankel structure
- perform a singular value decomposition
- and detects iteratively large residuals
- that are locally inconsistent

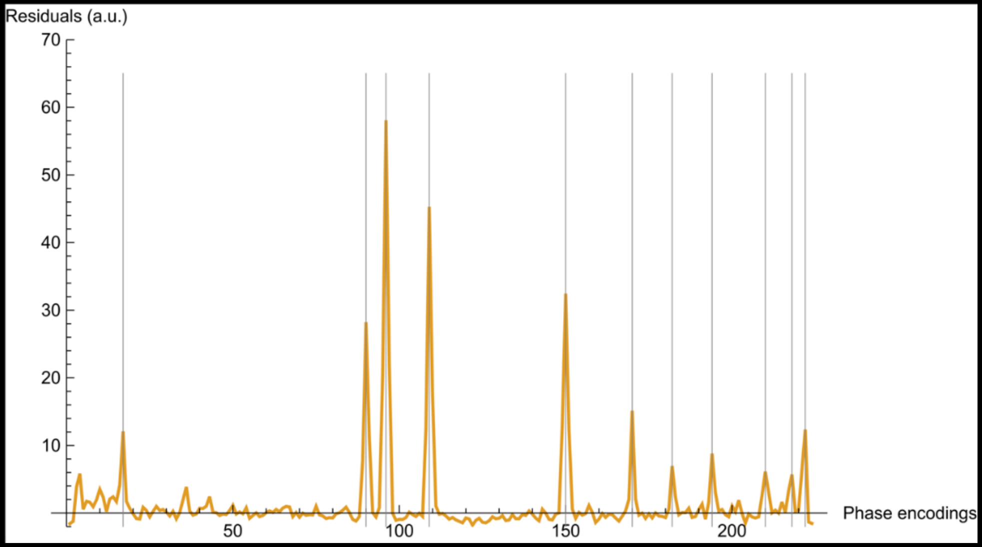
➢In many ways, it is similar to CNN models learning redundancy in the data, with residual connections, and binary classification (Motion / no motion)
➢AI is thus pertinent to be adapted/used to perform this classification task

Trimmed autocalibrating k-space estimation based on structured matrix completion

Bydder et al, Magn Reson Imagong, 2017, 10.1016/j.mri.2017.07.015

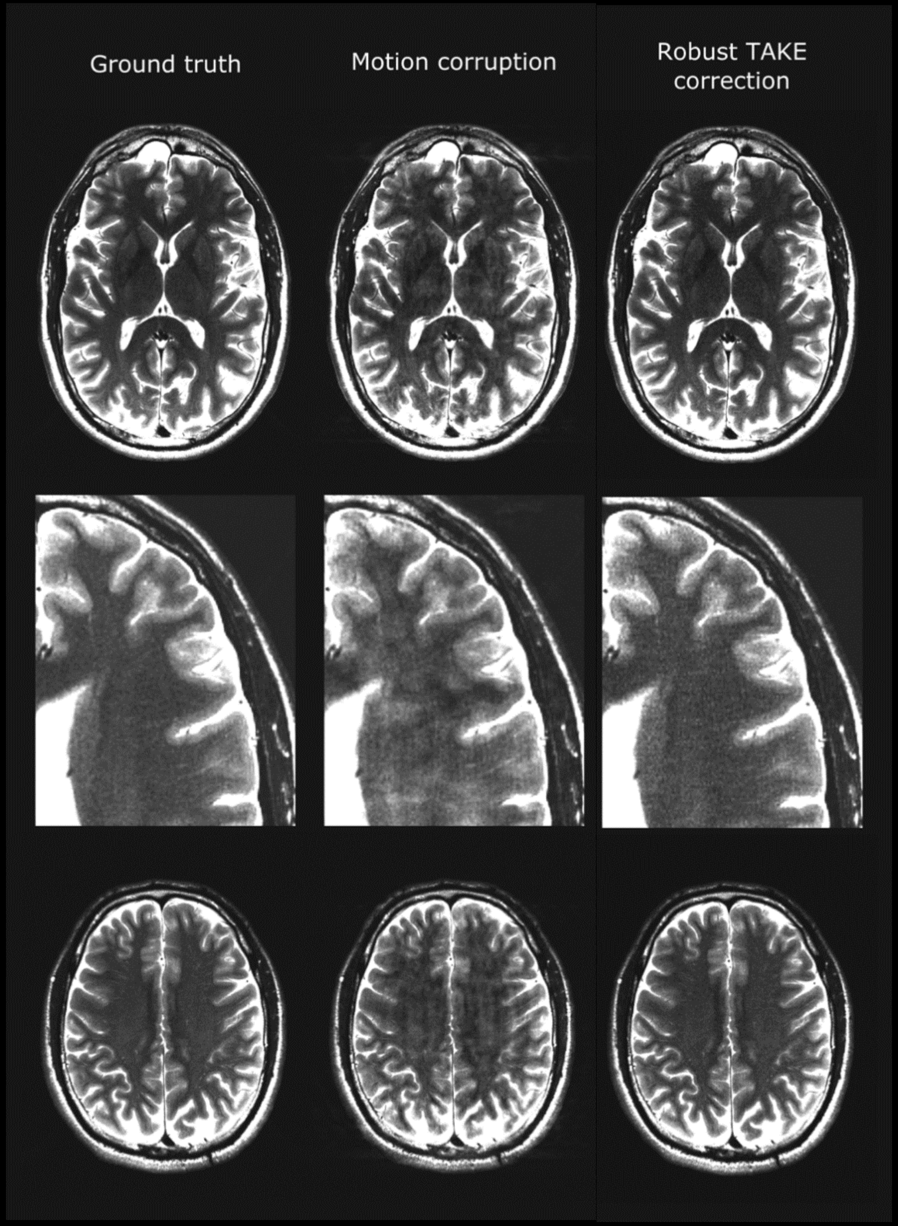
Models for the detection of motion corrupted line





Beaumont et al, ISMRM 2022

T2W 2D FSE on a volunteer



Reduction of motion artifacts

Conclusion

- High resolution / multiple contrasts / long scan
- High sensitivity to motion / cannot be sampled exhaustively
- Tasks that MRI-specific AI models can solve:
  - Scan–specific (considering one scan as the training database)
  - Adapted to the nature of MRI (high dimensions, space, contrasts, sensors, time, …)
  - Highly redundant

  - ➢ Super-resolution in k-space
  - ➢ Classification of motion-corrupted data

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